

# **UNDERSTANDING THE LOW VOLATILITY ANOMALY IN THE SOUTH AFRICAN EQUITY MARKET**

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## Abstract:

The Capital Asset Pricing Model (CAPM) advocates that expected return has a linear proportional relationship with beta (and subsequently volatility). As such, the higher the systematic risk of a security the higher the CAPM expected return. However, empirical results have hardly supported this view as argued as early as Black (1972). Instead, an anomaly has been evidenced across a multitude of developed and emerging markets, where portfolios constructed to have lower volatility have outperformed their higher volatility counterparts as found by Baker and Haugen (2012). This result has been found to exist in most Equity markets globally. In the South African market the studies of Khuzwayo (2011), Panulo (2014) and Oladele (2014) focused on establishing whether low volatility portfolios had outperformed market-cap weighted portfolios in the South African market. While they found this to be the case, it is important to understand if this is truly an anomaly or just a result of prevailing market conditions that have rewarded lower volatility stocks over the back-test period. As such, those conditions might not exist in the future and low volatility portfolios might then underperform. This research does not aim to show, yet again, the existence of this 'anomaly'; instead the aim is to dissect if there is any theoretical backing for low volatility portfolios to outperform high volatility portfolios. If this can be uncovered, then it should help one understand if the 'anomaly' truly exists and also if it can be expected to continue into the future.

Keywords: Beta, Alpha, Benchmarking, Arbitrage, Manager Compensation, Information Ratio, Analyst Forecasts, Analyst Growth Forecast Bias, Earnings Variability, Investor Overconfidence, Positive Skewness.

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## 1. Introduction

In international literature the low volatility anomaly is described as the empirical finding that low volatility stocks have outperformed high volatility stocks out-of-period (see Ang, Hodrick, Xing and Zhang (2008), Baker, Bradley and Taliaferro (2014), Clarke, de Silva and Thorley (2011) among others). Baker and Haugen (2012) argue that this finding is remarkable given that it is persistent, comprehensive and contradicts the core of finance theory that risk taking can be expected to produce reward.

Haugen and Heins (1972) produced a working paper covering the period 1926 to 1971 addressing the shortfalls of the previous studies regarding the relationship between risk and realized return. In fact, Haugen and Heins (1972) found a negative relationship between risk and realized return in the U.S. stock and bond markets. Baker and Haugen (2012) argue that the fact that this finding is prevalent today and its existence can be evidenced as far back as the early 1900's is evidence of the persistence of the low volatility anomaly. To test the comprehensiveness of the low volatility anomaly Baker and Haugen (2012) performed a back-test of low vs. high volatility portfolios in the largest 21 developed and largest 12 emerging markets globally (including South Africa). They found the low volatility portfolios to outperform the high volatility portfolios in all of these markets at a considerably lower risk out-of-period.

In the South African market Khuzwayo (2011), Panulo (2014) and Oladele (2014) constructed low volatility portfolios using different portfolio construction methodologies. While the above studies support the low volatility anomaly in the South African market, they were rather focused on analysing the low volatility portfolios relative to the market-cap weighted benchmarks and understanding the differences between the different low volatility portfolio construction methodologies. This thesis is materially different to the studies of Khuzwayo (2011), Panulo (2014) and Oladele (2014) in the following ways:

1. In this thesis the focus will be on the low volatility portfolios relative to high volatility portfolios (as opposed to market-cap weighted portfolios) in the South African market. This will ensure that the low volatility performance metric is consistent with international literature.
2. The main aim is to understand the potential causes of the low volatility anomaly by assessing arguments found in international literature and establishing if these arguments are relevant in the South African environment (see Baker and Haugen (2012), Hsu, Kudoh and Yamada (2013) and Baker, Bradley and Wurgler (2011) among others). Thus the aim will be to find empirical evidence in the South African market, if any, that is supportive of the causes of the low volatility anomaly as described in international literature.

If the potential causes of the low volatility anomaly can be uncovered in the South African market it should help one understand if it can be expected to continue into the future.

## 2. Literature Review

The CAPM advocates that expected return has a linear proportional relationship with beta (and subsequently volatility). As such, the higher the systematic risk of a security the higher the CAPM expected return. However, in practice an anomaly that has been found over decades of research in the financial markets has been that low volatility stocks have outperformed high volatility stocks globally out-of-period (see Ang, Hodrick, Xing and Zhang (2008), Baker, Bradley and Taliaferro (2014), Clarke, de Silva and Thorley (2011)). Over the years extensive research has gone into identifying if the anomaly exists and the potential causes of it. Haugen and Heins (1972) produced a working paper in which they addressed deficiencies in prior studies about the relationship between risk and realized return. One of their main findings was that a negative relationship between risk and return in the U.S. stock as well as bond markets has persisted.

In 1972 Fischer Black put forward an interpretation of why low risk stocks might outperform high risk stocks. He attributed this anomaly to an agent mispricing arising from borrowing restrictions (e.g. margin requirements). One of the key assumptions of the CAPM is that of unrestricted risk-free borrowing and lending. This is an unrealistic assumption in practice and as such Black (1972) developed a version of the CAPM without risk-free borrowing or lending. The interpretation of the agent mispricing problem is defined by Frazzini and Pedersen (2014) as follows: Some agents cannot use leverage, and as a result they overweight high beta stocks. On the other hand, some agents who can use leverage would underweight high beta securities and buy low beta securities and lever these up; however Frazzini and Pedersen (2014) argue that these agents face margin constraints. The slope of the security market line would then be flatter than that implied by the CAPM, depending on the funding constraints across agents. This is further supported by the findings of Brennan (1993) that suggested that limits to arbitrage may create a security market line that is flatter than predicted by the CAPM. All in all, this suggests that the realized return vs. beta relationship could be overstated by the CAPM if one takes into account the market limitations and constraints.

Since the early studies were conducted, the existence of a low beta / volatility anomaly is now almost an accepted phenomenon. Over the past few decades many studies have been conducted yielding evidence of this anomaly. It has proven to be existent and persistent in markets globally, both developed and emerging. While a lot of work has gone into back-tests which have ultimately shown support for this anomaly, not as much has gone into explaining why this would theoretically exist. In this research the aim is to pay more attention into why this anomaly exists and to find the potential theoretical backing for it, if it exists.

Baker, Bradley and Taliaferro (2014) are among the many researchers who have examined the low beta anomaly. They also found stocks with a lower beta (and subsequently lower volatility) to have outperformed those with a higher beta. They found that to be the case in



the U.S and in 31 developed equity markets over the periods 1968 to 2012 and 1989 to 2012 respectively. They then decomposed the low beta anomaly into micro and macro selection effects. Their definition of micro selection involves selecting low beta (volatility) stocks within industries (or countries); while macro selection involves selecting low beta (volatility) industries or countries. They found that, *ex ante*, low or high beta (volatility) stocks, industries or countries have low or high betas (volatilities) respectively out-of-period. This finding suggests that betas (volatilities) estimated from past returns are strong predictors of future betas (volatilities) at the stock, industry and country level. More importantly, they found that the low beta anomaly is more prevalent at the micro level (i.e. at stock level within industries and within countries) than at the overall industry or country level. They attribute this to the fact that individual securities have close substitutes, in most cases, making it easy to find arbitrage opportunities at the stock level. However, the same cannot be said of the industry and country portfolios as these do not have as close substitutes. Given that the contributors to overall volatility are the market effect and the idiosyncratic effect, the authors also back-tested the idiosyncratic risk. They found that stocks with low idiosyncratic risk have outperformed those with a high idiosyncratic risk. Again, they found the relationship to be more pronounced at the stock level than at the industry or country level.

Clarke, de Silva and Thorley (2011) showed that a minimum variance portfolio (constructed of the largest 1000 U.S. stocks) outperformed the market over the period 1967 to 2009. Their findings are consistent with the studies that have been cited and other international studies into low volatility portfolios. They then go into the mathematics of the minimum variance portfolio using Sharpe's single-index assumption that the only source of common risk across equity securities is a single factor (i.e. the market portfolio). They analytically then solve the formula for stock weights in an unconstrained minimum-variance portfolio. In addition, they also rearrange the formula for the optimal stock weights in a long-only minimum variance portfolio. The derivation asserts that a stock's weight is dependent on its beta relative to a threshold beta (i.e. their formulation only includes stocks with a beta less than the threshold beta). In addition their formulation down-weights stocks with a high idiosyncratic risk. The down-weighting of the idiosyncratic risk is consistent with the findings of Ang *et al.* (2008) who documented the low risk – high return anomaly attributable to idiosyncratic risk. The authors show that there is a positive relationship between beta and idiosyncratic risk. As such the formulation firstly identifies low beta stocks (i.e. stocks with betas less than the threshold beta) and then assigns weights depending on each stock's idiosyncratic risk. Overall, the strategy targets stocks with an overall low volatility (i.e. low systematic risk and low idiosyncratic risk).

In the South African market Khuzwayo (2011) back-tested the model introduced by Clarke *et al.* (2011) and contrasted the results with other traditional low risk portfolios and a market-capitalisation (market-cap) weighted benchmark in the South African setting. His findings were consistent with those found in global literature where lower volatility portfolios outperformed the market-cap weighted portfolios at a lower risk. In addition, he found the portfolio constructed using the methodology introduced by Clarke *et al.* (2011) to give the best return at the lowest risk in the South African setting. He found this portfolio to have the lowest drawdown relative to the other portfolios he had constructed which included minimum variance, equally weighted benchmark, market-cap weighted benchmark, equal

risk contribution and a portfolio constructed of stocks with the lowest possible correlations between stocks. Oladele (2014) also found the low volatility portfolio constructed using the Clarke *et al.* (2011) methodology to possess superior out-of-period risk and return characteristics than the other low volatility portfolios.

Baker and Haugen (2012) also found low volatility stocks to outperform high volatility stocks in 21 developed countries and in emerging markets at a lower risk. One of their logical explanations as to the existence of this phenomenon is the compensation of fund managers (i.e. where fund managers are measured on the information ratio and also receive a performance bonus for performance above a threshold). For example, if two stocks have the same expected return and one of them has a high beta and the other a low beta to the benchmark index, a manager who aims to maximise information ratio may avoid the lower beta stock if it increases the active risk (i.e. tracking error) more than the higher beta stock. As such these managers may have no incentive to hold low beta stocks with positive alphas, resulting in a flattening of the security market line. Further, low volatility portfolios exhibit less fat tails on both the upside and the downside. The less fat tails on the upside would imply that a manager who is compensated on a performance fee would reduce their probability of obtaining a performance fee if they are invested in low beta stocks. As such these managers may take on higher volatility to increase their probability of obtaining a performance bonus. These arguments by Baker and Haugen (2012) tie in very well with another important finding; that lower volatility stocks have less analyst and media coverage than higher volatility stocks. In addition, these stocks are held less by institutional investors than higher volatility stocks. This would then support the view that high beta stocks are generally priced at a premium relative to their low beta counterparts (i.e. low volatility stocks are generally priced at a discount relative to high volatility stocks). If this is the case, then that would explain why low volatility portfolios have outperformed the high volatility portfolios out-of-period. Importantly, that would also suggest that these should continue to outperform as long as they are priced at a discount relative to high volatility portfolios over the longer term.

Baker, Bradley and Wurgler (2011) attribute the low volatility anomaly to behavioural biases that afflict individual investors. They examined the following behavioural biases:

- I. *Investor preference for lotteries* – this behaviour they argue is about positive skewness where large positive payoffs are more likely than negative ones. However, there is a much larger chance of the investment producing a return below its mean. They argue that buying a stock with high volatility is like buying a lottery ticket where there is a small chance of it doubling or tripling in value in the short term; however, there is a much larger chance of it declining in relative value.
- II. *Representativeness* – to explain this they use an experiment by Tversky and Kahneman (1983) where they described a fictional woman named Linda who majored in philosophy as: single, outspoken and very bright. As a student she was very much concerned with issues of discrimination and social justice and participated in nuclear demonstrations. Tversky and Kahnemann (1983) then asked subjects which was more probable between:
  - a. *Linda is a bank teller*
  - b. *Linda is a bank teller who is active in the women's movement*

Interestingly, most subjects chose B relative to A. However, B is a subset of A and as such A is more probable than B. Baker *et al.* (2011) argue that the individual investors could think that the road to riches is paved with speculative investments in new technologies (e.g. identifying and buying stocks like Microsoft Corporation at their IPO's). However, the probability of identifying and buying good stocks at their IPO's is extremely low and as such a sophisticated investor would generally avoid speculative stocks.

- III. *Overconfidence* – valuing stocks involves forecasting stock revenues and earnings into the future (e.g. over the next 5 years). Baker *et al.* (2011) argue that overconfident investors will agree to disagree on their forecasts. Further, the extent of disagreement will likely be higher for more uncertain outcomes such as the forecasts for high volatility stocks. The extent of the differences in opinion, they argue, should then be reflected in the price where the optimists would buy the stocks while the pessimists would sell the stock. Baker *et al.* (2011) then argue that the scarcity of short sales among individual and institutional investors implies that pessimists act less aggressively than optimists in the markets. This would imply excess demand for high volatility stocks relative to low volatility stocks, making these stocks overvalued in the short term leading to lower subsequent returns.

Yamada and Nagawatari (2010) argue that the price volatility of a stock should reflect a company's earnings variability. They found stocks with high earnings variability to also possess high price volatility and vice versa. Furthermore, they found stocks with high earnings variability to have a higher earnings growth forecast error than those with low earnings variability. In a separate study, Hsu, Kudoh and Yamada (2013) found stocks with high earnings variability to possess higher growth forecast bias than those with low earnings variability. The fact that stocks with high earnings variability also possess high growth forecast bias shows that analysts are more optimistic about the growth prospects of the stocks with high earnings variability. Baker *et al.* (2011) argue that overconfident investors will not adjust the forecast growth for the stocks with high earnings variability. Hsu *et al.* (2013) argue that this overconfidence in growth forecasts for high volatility stocks causes investors to overreact to analyst optimism in the short run, causing volatile stocks to be overvalued. As a consequence, these would then experience low subsequent returns. On the other hand Hsu *et al.* (2013) further argue that analyst growth forecasts can still be informative and should not be dismissed entirely. In their study they found that stocks with high forward earnings yield outperformed those with a low forward earnings yield. Hsu *et al.* (2013) propose a model where the investor adjusts the analyst growth forecasts; in this adjustment stocks with high earnings variability get a higher adjustment than those with low earnings variability.

Baker *et al.* (2011) also argue that institutional investors who may want to take advantage of the low volatility anomaly struggle to do so because of the benchmarks that they are measured against. They argue that these benchmarks inherently force institutional investors to avoid low beta stocks given the tracking error these stocks would introduce to their portfolios, thus reducing their information ratio. They also demonstrate that low beta stocks require a larger expected alpha than high beta stocks to increase the expected information ratio of a portfolio. In fact their example shows that a low beta stock can decrease the expected information ratio of a portfolio even if it has a positive expected alpha to the

benchmark. On the other hand a high beta stock can still increase the expected information ratio even if it has a negative expected alpha to the benchmark. In essence they demonstrate that the required alpha hurdle (to increase the portfolio expected information ratio) increases as stock beta decreases, suggesting that the required alpha hurdle is higher for low beta stocks. Thus from a portfolio construction perspective, institutional investors would find it harder to invest in low beta stocks than high beta stocks. This would imply higher demand for high beta stocks relative to low beta stocks causing these stocks to be overvalued in the short-term leading to lower subsequent returns.

Baker and Wurgler (2006) define investor sentiment as the propensity to speculate, such that high positive investor sentiment implies a high propensity to speculate and vice versa. They found speculative stocks (i.e. small stocks, high volatility stocks, unprofitable stocks, etc.) to underperform safer stocks (i.e. older stocks, low volatility, profitable stocks, etc.) if the starting investor sentiment was high. This indicates that speculative stocks are overpriced during periods of high positive market sentiment. On the contrary, periods of low investor sentiment can be accompanied by a flight-to-safety. Caballero and Kurlat (2008) found the low investor sentiment market environment to be characterised by a decrease in demand for risky securities leading to a drop in their price or liquidity or both. In the equities space this market environment could be characterised by investors selling out of risky stocks and buying safer stocks. Brunnermeier and Pedersen (2009) showed that traders become reluctant to take on positions when funding liquidity is tight, particularly in high-margin securities. When speculators hit their capital constraints (or risk hitting their capital constraints over the life of a trade) they reduce their positions leading to a decline in market liquidity. Further they show that the margin requirement of a stock is proportional to its volatility. This implies that during periods of high volatility speculators have to put up higher margin to enter and keep a position. As such speculators could be forced to reduce their positions in this market environment, reducing market liquidity. Secondly, speculators are more likely to hit their capital constraints over the life of a trade with high volatility stocks than low volatility stocks all else equal. As such, during periods of high market volatility one would expect speculators to be reluctant to take large positions in high volatility stocks given their margin requirements. This implies that one would expect the high volatility stocks to have higher drawdowns than their low volatility counterparts during periods of market turmoil. This ties in well with the assertion that low volatility portfolios have lower drawdowns than high volatility portfolios and can thus recover more quickly from these (see Papathanakos and Musolf (2014) and Liu (2014)). In the South Africa market Khuzwayo (2011) found low volatility portfolios had considerably lower drawdowns than market-cap weighted portfolios, consistent with international findings.

Li, Sullivan and Garcia-Feijoo (2014) examine if the low volatility anomaly can be attributed to market mispricing or compensation for higher systematic risk. They assert that if the anomaly is related to systematic risk, then the outperformance can be attributed to some (as of yet) unknown common risk factor. Alternatively it may be driven by a mispricing such as investor irrationality regarding volatility. In contrast to Ang *et al.* (2008), the authors find that the outperformance can be best explained by a market mispricing associated with certain characteristics present in low volatility stocks as opposed to some pervasive risk factor. In other words, empirical evidence suggests that volatility in the market has

historically been mispriced. Looked at in another way one could say that investors have paid a premium for high volatility stocks.

The CAPM assumes that an investor uses volatility as a measure of risk and will always prefer lower volatility for a given expected return. Using the definition of volatility as the standard deviation of returns from the mean, this does not distinguish between positive and negative deviations from the mean. Tversky and Kahneman (1991) showed the loss aversion effect; where loss aversion implies that the loss of utility associated with giving up a valued good is greater than the utility gain associated with receiving it. Kahneman, Knetsch and Thaler (1991) give the following example to illustrate this:

*A wine loving economist they knew purchased Bordeaux wines at very low prices years ago. Since then wines have appreciated significantly in value; as such a bottle that one would have purchased for \$10 back in the day could now be sold at \$200 at an auction. The economist still drinks some of that wine occasionally. However, he would not be willing to sell his wine at the auction price nor be willing to buy an additional bottle at that price.*

This implies that value appears to change when a good is incorporated into one's endowment. As such Thaler (1980) called this discrepancy the endowment effect. The intuition behind loss aversion is that investors are more sensitive to losses (i.e. below a reference point) than they are to profits (i.e. above a reference point). This would imply a kink in the investors' utility curve as opposed to the usual continuous utility curves. This would also imply that below a certain threshold investors would demand a higher discount to make an allocation to a risky asset than that implied by the CAPM. Consequently, below a certain threshold the CAPM would potentially understate the required return by investors to invest in a stock. As such, a need potentially arises for a CAPM model that will take into account the loss aversion effect.

Reed, Tiu and Yoeli (2008) highlight the importance of managing downside risk. They highlight the shortcomings of using standard deviation of returns as the measure of risk. In particular, this measure assumes that the returns are symmetrical. It has been shown that returns for financial assets are not necessarily symmetrical. In fact, for some asset classes the return distributions are asymmetrical. Thus, it makes sense to look at a measure that focuses on the downside risk of asset classes. They come with a measure that defines risk as the downside deviation of asset returns (i.e. returns below a targeted threshold return). They found that including other asset classes (e.g. hedge funds) in one's portfolio helped improve returns while also reducing the downside risk of the portfolios. They also point out the importance of managing downside risk especially in cases where the investor needs to withdraw from the investment.

In recent years extensive research has gone into a downside beta CAPM. This version of the CAPM captures most of the features of the CAPM but does not include the assumptions of normality and the uniform investor preference for both upside and downside risk. Estrada (2007) concluded that semi-variance is a more plausible measure of risk than the traditional variance. He also concluded that this can be used to generate an alternative mean – semi-variance behaviour as opposed to the traditional mean-variance behaviour. This also introduced downside beta as an alternative risk measure for investors and an alternative pricing model based on the downside beta. To highlight the importance of including

downside risk, Chong and Phillips (2012) proposed a CAPM version with a dual beta model which differentiated between up and down market betas. They showed how the discount rate used in valuing companies can change depending on whether one uses regular CAPM relative to their DCAPM (downside beta CAPM) model. They then showed how the final valuation of a company can change materially, depending on the final discount rate used. In other words, the beta used in the CAPM is an important component of the final decision to buy or sell a security. As such the beta component in the CAPM is of central importance.

If investors are, in fact, more sensitive to losses than they are to profits on the upside then a measure of downside risk ought to be considered in the pricing of securities (as opposed to the universal beta). Ang, Chen and Xing (2002) studied the relationship between downside correlation and subsequent stock returns. They argue that conditional correlations would do a better job at capturing asymmetries in risk than conditional betas. This can be attributed to the fact that conditional correlations are unaffected by different idiosyncratic and market volatility in upside and downside market movements. They found a significant positive relationship between downside correlation and subsequent returns. The portfolios with the highest downside correlations had significantly higher returns than portfolios with lower downside correlation out-of-period. They also found a monotonic relationship between downside correlation and subsequent returns. While they did find a positive relationship between downside beta and subsequent return, it was not found to be statistically significant. On the other hand, they found no relationship between upside beta and correlation to subsequent returns. This would then support the assertion that investors are more sensitive to downside risk than they are to upside return.

Ishibe, Kakuta and Sakamaki (2011) performed a similar analysis in the Japanese stock exchange but their analysis used volatility as opposed to correlation. They found portfolios constructed using the stocks with high downside volatility outperformed those with lower downside volatility. Their test period was over 1990 to 2010. Breaking down the periods into 5 year periods, they found this relationship to be statistically significant over all 5 year periods except the period 1995 to 1999. Over all other periods the relationship is almost monotonic. They found the relationship to break down if one uses upside volatility or the traditional volatility measure. This would also support the notion that the CAPM overstates risk on the upside and understates investors risk preferences on the downside. Galagedera and Brooks (2005) also had a similar finding while back-testing a multitude of emerging markets, using downside beta as opposed to correlation and volatility. Secondly, their analysis was done at the country level as opposed to the stock level. They found portfolios consisting of the highest downside beta emerging market countries outperformed the low downside beta emerging market countries. However, they also found portfolios of high beta emerging market countries to have outperformed their low beta counterparts. This finding is consistent with that of Baker *et al.* (2014) who found the low beta anomaly to be more pronounced at the micro level than the macro level.

### 3. Research Aim

The aim of this thesis is to:

- Create low volatility portfolios in the South African setting
  - a. These portfolios will include portfolios created to minimise overall volatility, minimise idiosyncratic risk and also low beta.
  - b. The performance will be tested to detect if the performance is as a result of sector biases or because of a low beta anomaly. To achieve this in the South African setting the methodology followed is a modified version of the methodology of Baker, Bradley and Taliaferro (2014).

Importantly, the aim of this research is not just to back-test the performance of low volatility portfolios. Rather, it is to understand the performance of these portfolios and to explain why they have outperformed. Importantly, the aim is to understand if this can be expected to continue into the future. As such the focus of this research will be on the understanding of the drivers of the outperformance.

- Once the back-test results have been obtained, an extensive analysis of the portfolios will be performed over time. This analysis should help with the understanding of the rationale for the outperformance of these portfolios.
  - a. The paper by Baker and Haugen (2012) will be followed closely in meeting this aim. The arguments put forward by the authors will be introduced and back-tested in the South African market.
  - b. The arguments put forward by Baker, Bradley and Wurgler (2011) which relate to behavioural biases of investors and benchmarks exacerbating the low volatility anomaly will also be back-tested in the South African market.
  - c. Papathankos and Musolf (2014) and Liu (2014) argued that low volatility portfolios have lower drawdowns than high volatility portfolios and can thus recover more quickly from losses. This argument will also be back-tested in the South African market.

Ultimately it is hoped that the research will reveal if risk has been mispriced in the South African market. In addition, this should help to establish if the low volatility anomaly truly exists and if it can be expected to continue into the future.

#### 4. Back-testing the low volatility anomaly in the South African market

The Capital Asset Pricing Model (CAPM) advocates that a security's expected return can be attributed to its market beta as shown below (see Sharpe (1964), Abbas, Ayub, Sargana and Saeed (2011), Fama and French (2004), etc.):

$$E[R_i] = R_f + \beta_i E(R_{mkt} - R_f) \quad (1)$$

where  $E[R_i]$  = expected return on asset  $i$

$R_f$  = risk – free rate

$\beta_i$  = beta of asset  $i$  to the *market*

$R_{mkt}$  = expected *market* return

Given that the risk-free rate and the expected market return are constants in (1) at a point in time, this relationship implies that the main determinant of a security's expected return is its beta to the market index. In addition, it implies that the higher the beta of a security the higher the expected return. As such, if one were to construct a portfolio consisting of high beta vs. low beta shares the expectation would be for the high beta portfolio to outperform the low beta portfolio.

Following from the above is the assertion that investors are expected to be rewarded according to the systematic risk they are willing to take (i.e. the higher the beta risk, the higher the reward). Thus, investors cannot expect to be compensated for bearing extra unsystematic (idiosyncratic) risk as this risk can be diversified away in a portfolio.

The total portfolio risk (variance) can then be decomposed into systematic risk and unsystematic risk components as follows (see Bradfield (2000)):

Total Risk = Systematic Risk + Unsystematic Risk

$$\sigma_p^2 = \beta_p^2 \sigma_{mkt}^2 + \sigma_{p,\epsilon}^2 \quad (2)$$

where  $\sigma_p^2$  = variance of portfolio  $P$

$\beta_p$  = beta of portfolio  $P$  to the *market*

$\sigma_{mkt}^2$  = variance of the *market* portfolio

$\sigma_{p,\epsilon}^2$  = idiosyncratic risk of portfolio  $P$

From equation (2) above it follows that higher beta and idiosyncratic risk imply higher total portfolio risk (variance). Thus, from equation (1) and (2) it follows that higher beta implies higher risk and higher expected return *ceteris Paribus*. In reality, though, this has been found not to be the case. In fact, academic literature dating back to Black (1972) has found empirical evidence that low beta portfolios have outperformed high beta portfolios. What is more compelling about this result is that it has been found to be persistent in the majority



of equity markets in both the developed and emerging markets as shown by Baker and Haugen (2012). This stands in stark contrast to the CAPM expectation, which asserts that investors are expected to be rewarded according to the level of systematic risk they are willing to take. This finding has also been observed in the South African setting as shown by Khuzwayo (2011), Panulo (2014) and Oladele (2014). It is important to understand if this is, in fact, an anomaly or if it could be attributed to certain characteristics of the low volatility portfolios that just worked well over the back-test period (e.g. they could have over-weighted a low beta sector that performed well over the back-test period).

## 4.1.Data and Methodology

### Methodology:

For the purposes of this research there is a need to define what is meant by low volatility portfolios. The most obvious and widely used low volatility portfolio construction technique is the global minimum variance (GMV) portfolio (see Chow, Hsu, Kuo and Li (2014)). Ex-ante this portfolio comprises of risky assets such that it is expected to have the lowest volatility along the efficient frontier. This is the only portfolio on the efficient frontier that is constructed without expected return inputs. The GMV is calculated as shown below:

$$\begin{aligned} \min \sigma_p^2 &= w' \Sigma w \\ \text{s.t. } \sum_{i=1}^n w_i &= 1 \text{ and } w_i \geq 0 \text{ for } i = 1, \dots, n \end{aligned} \quad (3)$$

where  $\Sigma = n \times n$  covariance matrix

$w = n \times 1$  vector of security weights

From (3) it follows that the GMV portfolio, by construction, is supposed to encompass all the aspects of minimising volatility. By construction this portfolio is supposed to jointly reduce portfolio concentration, exploit correlation properties of the securities and also find stocks with the lowest volatilities. In reality, however, this portfolio construction technique is found to have some serious unwanted shortcomings as it can lead to undiversified portfolios. Instead of exploiting the correlation structure in the market, the GMV portfolio optimisation leads to highly concentrated portfolios (see Maillard, Roncalli and Teiletche (2010) and Amenc, Goltz and Stoyanov (2011)) which are typically concentrated in low volatility stocks. In the South African setting the GMV was also found to possess high levels of concentration in low volatility stocks as was found by Khuzwayo (2011) and Panulo (2014). Lee (2011) argues that although the GMV is expected to have the lowest volatility, it does not necessarily suggest that it is diversified from the standpoint of the asset weights within the portfolio. He notes that the asset weights in this portfolio can be very sensitive to the estimates of both volatilities and correlations.

Given the shortcomings of the GMV portfolio optimisation, other low volatility portfolio construction methodologies have been introduced in international literature. These low

volatility portfolio construction methodologies target specific shortcomings of the low volatility portfolio. Some of the more popularly known low volatility strategies are listed below and their advantages and disadvantages are discussed.

### **A: Equally weighted portfolio**

#### **Description:**

In this construction technique one allocates an equal weight to all the stocks in the benchmark. The security weights in this methodology are defined as shown below (see Maillard, Roncalli and Teiletche (2010) and Plyakha, Uppal and Vilkov (2012)):

$$w_i = \frac{1}{n} \text{ for } i = 1, \dots, n \quad (4)$$

where  $n$  = total number of securities in the portfolio

This low volatility portfolio construction technique negates the weight concentration inherent in the GMV portfolio as it yields the lowest possible weight concentration (i.e. the highest possible weight diversification) for a given benchmark.

#### **Pros:**

- Gives the most diversified portfolio at the stock weights level.
- Achieves reduced volatility relative to the market-cap weighted benchmark as a result of the weight diversification.

#### **Cons:**

- Does not take into account the correlation structure between the assets.
- Does not take into account the individual asset volatilities.
- Does not explicitly target to reduce volatility; thus it may include assets with high volatilities and high correlations.

### **B: Equal Risk Contribution portfolio (ERC Portfolio)**

#### **Description:**

Maillard *et al.* (2010) introduced the construction technique whose aim is to maximise risk diversification by ensuring that all assets in the portfolio have an equal contribution to the overall risk of the portfolio. The optimal security weights in the Maillard *et al.* (2010) risk-parity setting are constructed by performing the following optimisation:

$$\begin{aligned} \min f(w) &= \sum_{i=1}^n \sum_{j=1}^n (w_i(\Sigma w)_i - w_j(\Sigma w)_j)^2 \\ \text{s. t. } w_i &\geq 0 \quad i = 1, \dots, n \text{ and } \sum_{i=1}^n w_i = 1 \end{aligned} \quad (5)$$

where  $\Sigma = n \times n$  covariance matrix  
 $w = n \times 1$  vector of security weights

The existence of a risk-parity portfolio is ensured only when the condition  $f(w^*) = 0$  is verified; in which case  $w_i(\Sigma w)_i = w_j(\Sigma w)_j$  for all  $i, j = 1, \dots, n$ . By construction this technique yields the lowest possible risk concentration.

**Pros:**

- Gives the most diversified portfolio in terms of asset contribution to total portfolio volatility.
- Takes into account the prevailing asset volatilities and correlations.
- Achieves reduced volatility relative to the market-cap weighted benchmark as a result of the maximum risk diversification.

**Cons:**

- Not easy to compute and at times may not find a solution.
- Does not explicitly target to reduce volatility; thus it may include assets with high volatilities and high correlations – but the weights of these will be reduced (unlike the equally weighted portfolio).

### **C: Maximum Diversification Ratio (MD Portfolio)**

**Description:**

Choueifaty and Coignard (2008) introduced the diversification ratio as a measure of portfolio diversification. This measure essentially gives the risk reduction in a portfolio achieved by including stocks with low correlations. To find the portfolio with the maximum diversification ratio Choueifaty and Coignard (2008) perform the following optimisation:

$$\max \text{Diversification Ratio} = D(W) = \frac{w' \Omega}{\sqrt{w' \Sigma w}} \quad (6)$$

$$s. t. w_i \geq 0 \text{ for } i = 1, \dots, n \text{ and } \sum_{i=1}^n w_i = 1$$

where  $w = n \times 1$  vector of security weights

$\Omega = (\sigma_1, \dots, \sigma_n)' = n \times 1$  vector of security volatilities

$\Sigma = n \times n$  covariance matrix

This low volatility portfolio construction technique targets the correlation aspect of equation (3). In this technique the aim is to find stocks with the lowest correlation between each other.

**Pros:**

- Aim to maximise diversification in the traditional sense (i.e. adding uncorrelated assets to one's portfolio).
- Aims to exploit the correlation structure in the market by finding stocks that are least correlated to each other.
- Most diversified portfolio with respect to correlation as it finds the least correlated combination of stocks.

**Cons:**

- May yield to high concentration depending on stock correlations.
- Does not take into account the individual asset volatilities.
- Does not explicitly target to reduce volatility; thus it may potentially yield a portfolio of highly volatile stocks with low correlations amongst themselves.

**D: Clarke et al. (2011) Minimum Variance Portfolio (Low Vol SI- Model)****Description:**

Clarke, de Silva and Thorley (2011) introduced a low volatility portfolio construction technique that is very similar to the GMV. Clarke *et al.* (2011) argue that when stock return variations can be well described by a one factor model (i.e. using systematic risk), then the GMV portfolio can be approximated by a simpler methodology which calculates the portfolio weights as a function of CAPM beta. This method is derived from Sharpe's (1963) single-index assumption that only one source of risk is common across all securities, consistent with the CAPM. The minimum-variance optimisation in this setting is defined by Clarke *et al.* (2011) as follows:

$$w_i = \frac{\sigma_{LMV}^2}{\sigma_{\varepsilon i}^2} \left( 1 - \frac{\beta_i}{\beta_L} \right) \text{ for } \beta_i < \beta_L \text{ else } w_i = 0 \quad (7)$$

where  $w_i$  = weight of security  $i$

$\sigma_{LMV}^2$  = ex – ante variance of the long – only GMV portfolio

$\sigma_{\varepsilon i}^2$  = ex – ante idiosyncratic variance of security  $i$

$\beta_i$  = ex – ante market beta for security  $i$

$\beta_L$  = long – only threshold beta

**Pros:**

- Fairly easy to compute the optimal portfolio.
- Explicitly targets the components of the minimum variance portfolio in equation (3).
- The determinant of whether a security is included in the portfolio is its CAPM beta and whether or not it is less than the threshold beta.
- Underlying assumption is somewhat similar to the CAPM assumption that the driver of the expected security return is its CAPM beta.

- While the CAPM is expectations-based, Sharpe's (1963) single-index model assumes that the driver of a security's return (ex-post) is the market return and an idiosyncratic component.
- By construction the security weight concentration is less than the GMV portfolio.

**Cons:**

- Given its similarity to the GMV, this portfolio could still possess higher levels of weight concentration than the market-cap weighted benchmarks.
- If the explanatory power of the common factor in the market is very low, this portfolio construction technique would be a poor approximation of the GMV.

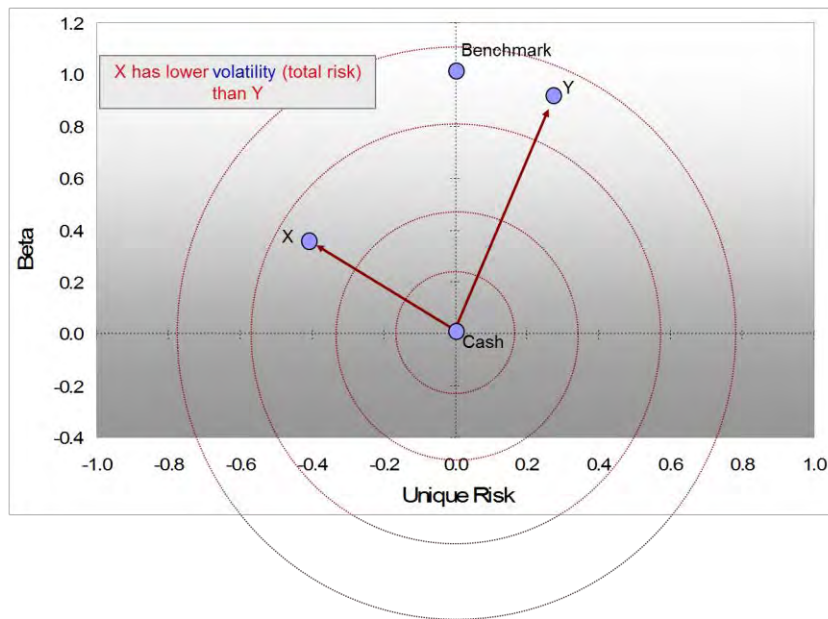
In the South African market Khuzwayo (2011), Panulo (2014) and Oladele (2014) compared the characteristics of these portfolios. To simultaneously compare the risk characteristics of the portfolios Khuzwayo (2011) plotted a covariance bi-plot using the out-of-period monthly returns of the portfolios. Barr, Underhill and Kahn (1990) were the first to use this technique in a Finance/ Economics setting. The appealing feature of the covariance bi-plot is that it allows one to condense the risk characteristics of assets into a 2 dimensional risk plot. Information is provided below on how to read some of the portfolio risk characteristics using the covariance bi-plot.

***Information on reading the covariance bi-plot***

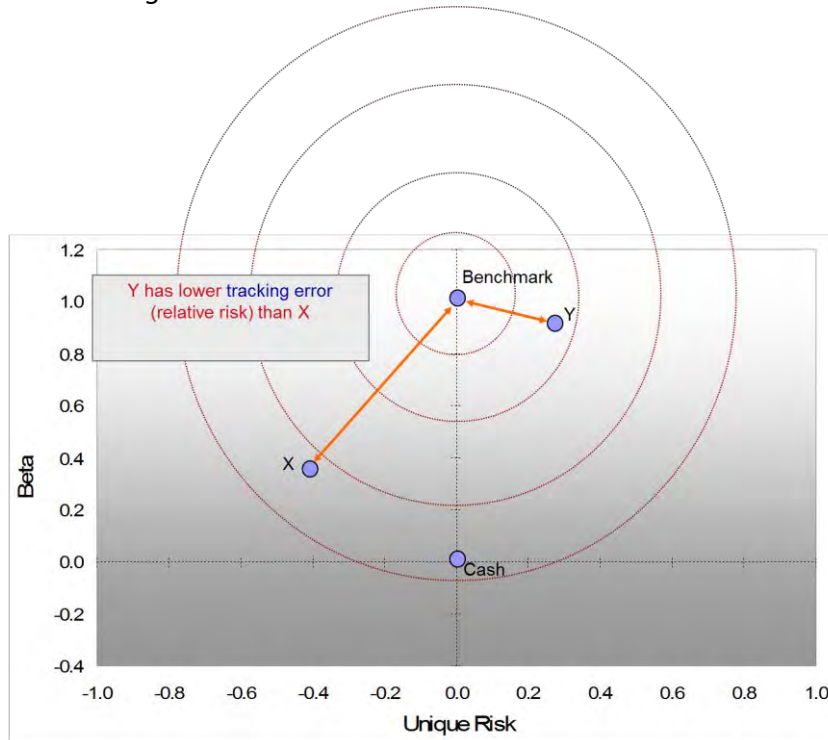
1. The starting point is that Cash is positioned at the co-ordinates  $(x, y) = (0, 0)$ .
2. Assume the y-axis gives the beta to a benchmark and the x-axis the unique risk relative to the benchmark. The sign of the unique risk is negligible and negative numbers should be thought of as being positive as the unique risk is always positive. The sign (i.e. positive or negative) of the unique risk is important for the positioning of the assets.
3. The benchmark positioning is at  $(x, y) = (0, 1)$ .

**Reading off risk characteristics from the covariance bi-plot**

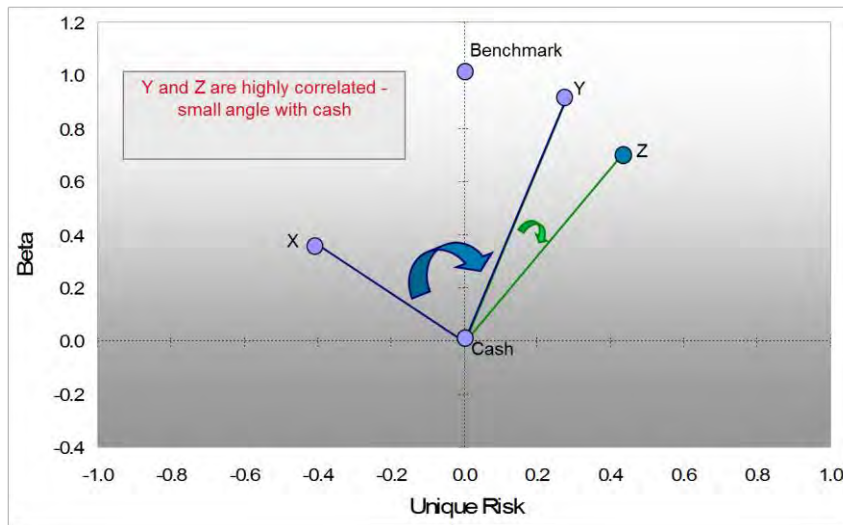
- *Beta*: y co-ordinate of the asset's position
- *Unique Risk*: absolute value of the x co-ordinate of the asset's position
- *Volatility*: distance between an asset and Cash



- *Tracking error: distance between asset and benchmark*

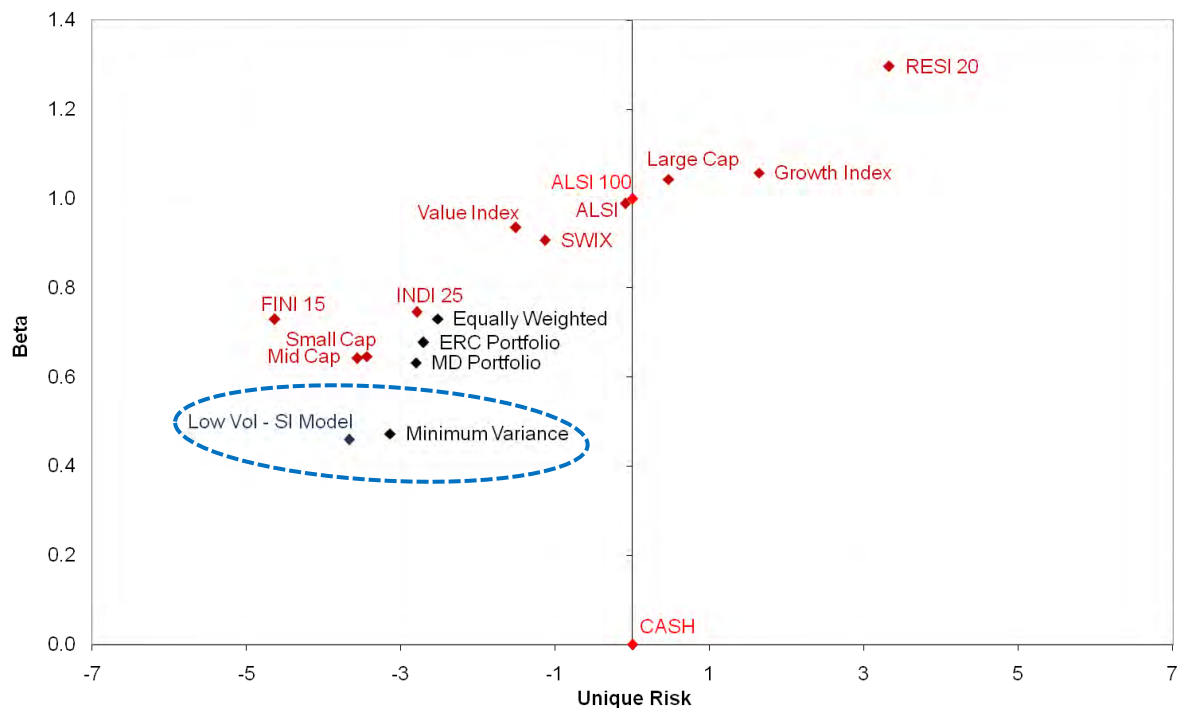


- *Asset Correlation*: cosine of angle between the lines connecting Cash and the 2 assets as shown below.



Khuzwayo (2011) used the covariance bi-plot in Figure 5.1.1 to compare the risk characteristics of the above-mentioned low volatility portfolio construction techniques in the South African market out-of-period.

**Figure 4.1.1: Covariance bi-plot of the low volatility portfolios (Khuzwayo (2011)):**



From Figure 4.1.1 the following observations were made regarding the low volatility portfolios in the South African market:

- The Low Vol SI Model (i.e. Clarke *et al.* (2011)) and the Minimum Variance (GMV) portfolios have similar betas (i.e.  $\pm 0.5$ ) to the benchmark (i.e. ALSI 100) while the Equally Weighted, ERC Portfolio and MD Portfolio have similar and higher betas to the benchmark.
- The Low Vol SI Model and the Minimum Variance portfolios have considerably lower volatility than the Equally Weighted, ERC Portfolio and MD Portfolio.
- The Low Vol SI Model and Minimum Variance portfolios are highly correlated out-of-period. Secondly, these portfolios have a lower correlation with the Equally Weighted, ERC Portfolio and MD Portfolio. On the contrary, the Equally Weighted, ERC Portfolio and MD Portfolio are highly correlated out-of-period.
- The Low Vol SI Model and Minimum Variance portfolios have a higher (but similar) tracking error to the ALSI and SWIX benchmarks than the Equally Weighted, ERC Portfolio and MD Portfolio.

From the above findings it is clear that the Low Vol SI Model (i.e. Clarke *et al.* (2011) minimum variance) and the Minimum Variance portfolios (i.e. GMV) are more distinct from the benchmarks (i.e. ALSI and SWIX) than the Equally Weighted, ERC Portfolio and MD Portfolio. Thus, to assess the low volatility anomaly the Low Vol SI Model and Minimum Variance portfolios are better candidates as they possess a more distinct low beta risk than the other methodologies.



The Clarke *et al.* (2011) methodology aims to mitigate some of the shortcomings of the GMV portfolio. Oladele (2014) found this low volatility portfolio construction technique to have superior risk-return characteristics than the other low volatility portfolios based on out-of-period Sharpe ratios. From Figure 4.1.1 the out-of-period risk characteristics of this construction technique are very similar to the GMV portfolio but with improved weight diversification (see Khuzwayo (2011)). Thus, the Clarke *et al.* (2011) methodology is a good approximation of the GMV portfolio out-of-period and also helps improve some of the unwanted characteristics of the GMV portfolio. Thus, the Clarke *et al.* (2011) methodology will be used in the remainder of this thesis as a proxy for a low volatility portfolio constructed in the South African environment.

In international literature the low volatility anomaly is described as the finding that low volatility portfolios tend to outperform high volatility portfolios at a lower risk, out-of-period (see Baker *et al.* (2014), Baker and Haugen (2012) and Frazzini and Pedersen (2014) among others). To test the existence of the low volatility anomaly in the South African market there is, thus, a need to construct a high volatility portfolio in this market. The high volatility portfolio will be constructed in a similar methodology to equation (7).

Clarke *et al.* (2011) calculate a threshold beta and all stocks with betas less than the threshold beta are assigned a weight in the low volatility portfolio. To construct the high volatility portfolio, only stocks with a beta higher than the threshold beta will be included in this portfolio over time. The security weights will be assigned in a similar way to equation (7) but stocks with a higher beta will be up-weighted as follows:

$$w_i = \frac{\sigma_{MaxV}^2}{\sigma_{\epsilon i}^2} \left( \frac{\beta_i}{\beta_L} - 1 \right) \text{ for } \beta_i > \beta_L \text{ else } w_i = 0 \quad (8)$$

where  $\sigma_{MaxV}^2$  = ex – ante volatility of *maximum volatility* portfolio

In essence the approach in (8) will include all the stocks that were excluded in the low volatility portfolio. Thus, there is no stock overlap between the two portfolios. Secondly, high beta stocks will be up-weighted in this portfolio. As such, the main differentiator between the low volatility and high volatility portfolios will be the individual stock betas and whether or not they are lower or higher than the threshold beta. The similarity with (7) is that stocks with a high idiosyncratic risk will still be penalised. This is consistent with the CAPM which asserts that there is no reward for bearing extra idiosyncratic risk and the findings of Ang *et al.* (2008).

In the South African market the low volatility anomaly will be tested using the low volatility and high volatility portfolios described above. For comparison purposes, these low and high volatility portfolios will also be analysed relative to the market-cap weighted benchmark in the South African market.

### Data:

The stock weights in the JSE All Share index (over time) were obtained from the BNP Paribas Cadiz Securities database. The total stock returns that will be used to construct the covariance matrix over time were also obtained from this database.

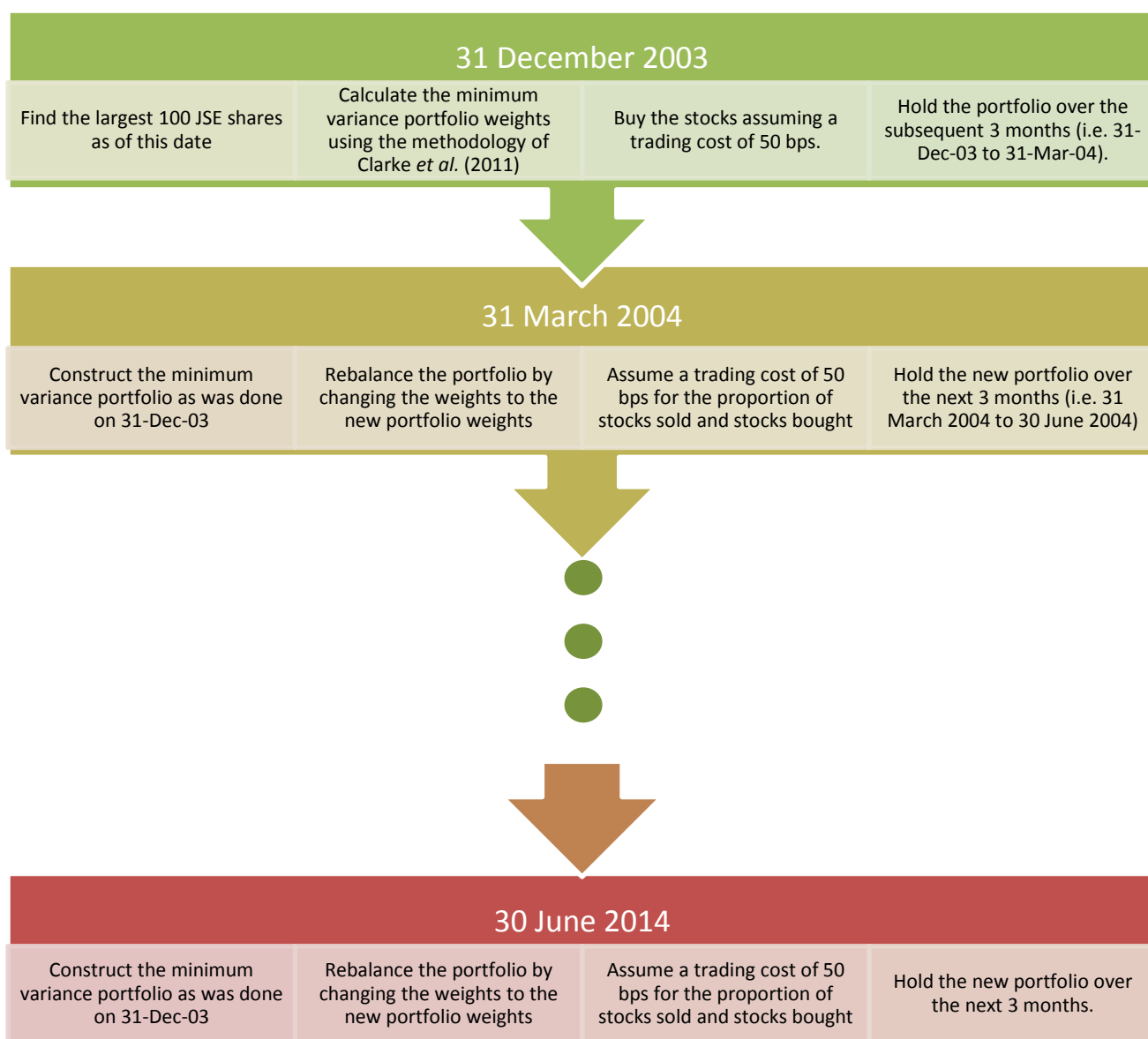
The back-test will be run over the period 31 December 2003 to August 2014 using the largest 100 JSE universe as a consideration for liquidity purposes.

At each quarter-end the low and high volatility portfolios will be constructed following the methodology explained below and are rebalanced quarterly.

A fairly aggressive transaction cost of 50 basis points (bps) is assumed upon rebalancing the portfolios. Given that the liquidity constraints and other trading costs have not been incorporated in the analysis; the fairly high transaction cost should negate some of the other considerations that have not been incorporated.

## 4.2. Back-test Results

The back-test was run as follows:



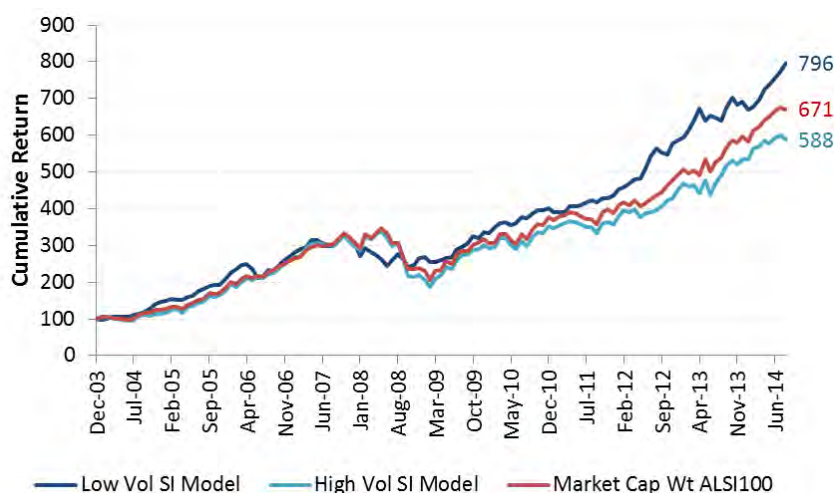
Below are the back-test results of the low and high volatility portfolios relative to the market-cap weighted ALSI 100.

#### 4.2.1. Back-test results using Top 100 JSE share universe

Figure 4.2.1.1 depicts the cumulative total returns of R100 invested in the low volatility, high volatility and market-cap weighted portfolios as at 31 December 2003 to 31 August 2014. On the figure the following abbreviations have been used:

- Low Vol SI Model (Clarke *et al.* (2011) minimum variance portfolio)
- High Vol SI Model (high volatility portfolio created using a derivation similar to Clarke *et al.* (2011))
- Market-cap Wt ALSI 100 (largest 100 JSE shares weighted according to their market-capitalisation)

**Figure 4.2.1.1: Cumulative Returns constructed using Top 100 JSE shares over time**



From Figure 4.2.1.1 it is evident that in the South African market; the low volatility portfolio has outperformed both the market-cap weighted benchmark and the high volatility portfolio over this period, consistent with international findings (see Clarke *et al.* (2011), Baker and Haugen (2012), Baker *et al.* (2014), Ang *et al.* (2008) among others).

Baker *et al.* (2014) perform a statistical test to determine if the low volatility alpha relative to the high volatility portfolio (i.e. low volatility – high volatility) is statistically significant using the market model. From the market model it can be deduced that the relative return of the low volatility portfolio (relative to the high volatility portfolio) can be depicted as follows:

$$R_{lowV,t} - R_{highV,t} = (\beta_{lowV} - \beta_{highV}) * (R_{mkt,t} - R_{f,t}) + (\alpha_{lowV} - \alpha_{highV}) + \epsilon_t \quad (9)$$

$$= \text{Net Low Vol Beta} * \text{Market Risk Premium} + \text{net low Vol alpha}$$

where  $R_{lowV,t}$  = return of low volatility portfolio at time  $t$

$R_{highV,t}$  = return of high volatility portfolio at time  $t$

$\beta_{lowV}$  = market beta of the low volatility portfolio

$\beta_{highV}$  = market beta of the high volatility portfolio

$R_{mkt,t}$  = return of the market portfolio at time  $t$

$R_{f,t}$  = risk – free rate at time  $t$

$\alpha_{lowV}$  = alpha of the low volatility portfolio

$\alpha_{highV}$  = alpha of the high volatility portfolio

Baker *et al.* (2014) found the low volatility portfolio to have a negative net (relative to the high volatility portfolio) market beta which was statistically significant. In other words, they found the beta of the low volatility portfolio to be statistically significantly less than that of the high volatility portfolio out-of-period. On the contrary they found the low volatility

portfolio to have a statistically significant positive alpha relative to the high volatility portfolio out-of-period.

Using this formulation, Table 4.2.1.1 depicts the market model regression performed on the low and high volatility portfolios in the South African market using monthly return data.

**Table 4.2.1.1: ANOVA table obtained from Low – High Volatility portfolio market model regression (December 2003 to August 2014)**

<i>Regression Statistics</i>	
Multiple R	64%
R Square	41%
Adjusted R Square	41%
Standard Error	3.64
Observations	128

ANOVA					
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	1	1 165.94	1 165.94	88.19	0%
Residual	126	1 665.83	13.22		
Total	127	2 831.77			

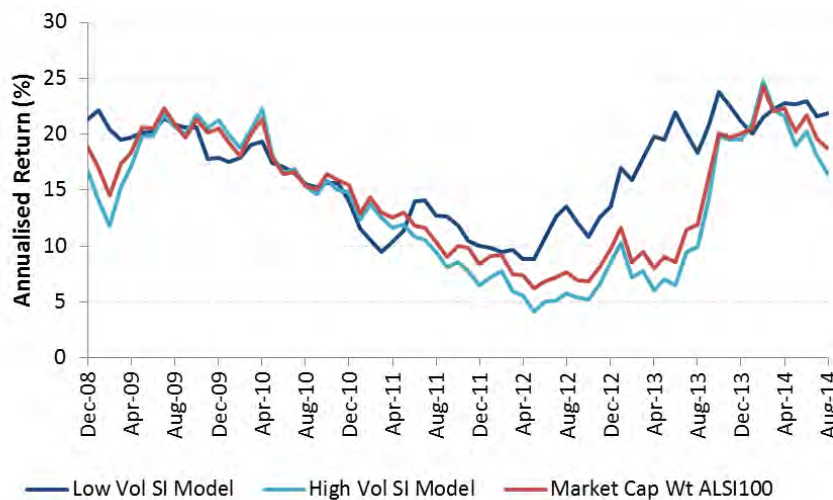
  

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
<b>Net Alpha (Low - High Vol)</b>	0.84	0.33	2.55	1%	0.19	1.49	0.19	1.49
<b>Net Beta (Low - High Vol)</b>	-0.66	0.07	-9.39	0%	-0.79	-0.52	-0.79	-0.52

From Table 4.2.1.1 the findings in the South African setting are consistent with those in international literature. The beta of the low volatility portfolio is statistically significantly (i.e. p-value of 0%) less than that of the high volatility portfolio by 0.66, out-of-period in the South African market. On the other hand the low volatility portfolio has had a statistically significant positive alpha of 0.84% relative to the high volatility portfolio out-of-period as shown by the p-value of 1%. Overall this market model regression explains 41% of the variation in the outperformance of the low volatility portfolio relative to the high volatility portfolio. From the above table the F-statistic is significant with a p-value of 0%. Thus it can be concluded that the above out-of-period market model regression is statistically significant.

The above results were achieved over the entire period but do not show the consistency of the outperformance over time. In Figure 4.2.1.2 the rolling 5 year returns of the portfolios are depicted, with the aim to determine the consistency of the low volatility portfolio outperformance relative to the high volatility portfolio.

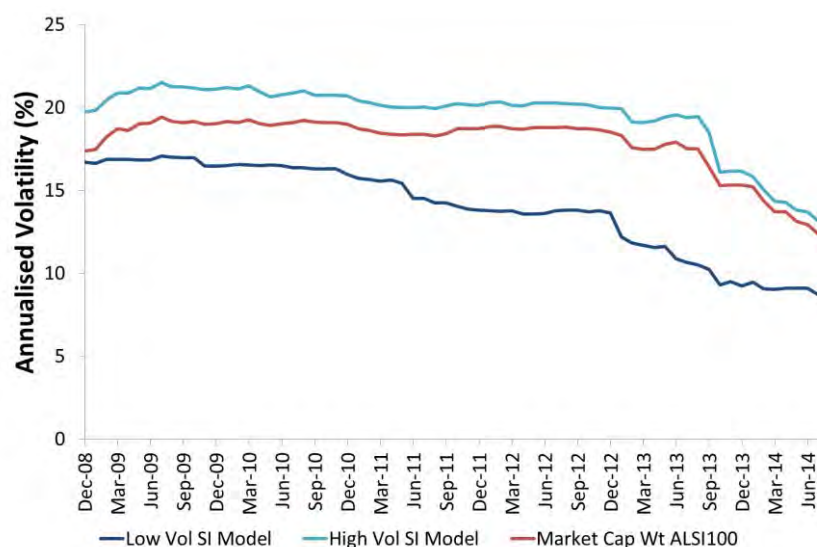
**Figure 4.2.1.2: Rolling 5 Year Returns constructed using Top100 JSE shares over time**



From Figure 4.2.1.2 it is evident that the outperformance has been achieved with reasonable consistency over time. On a rolling 5 year basis the low volatility portfolio has outperformed the high volatility portfolio and the ALSI 100, 72% and 67% of time respectively. This highlights the fact that the outperformance has been achieved fairly consistently over the long-term as opposed to there being one data point that has skewed the result.

International literature has found the low volatility portfolios to have outperformed the high volatility portfolios while preserving their low volatility characteristic out-of-period (see Baker *et al.* (2014), Baker and Haugen (2012) and Ishibe *et al.* (2011)). To test if the portfolios have preserved their risk characteristics out-of-period in the South African setting; Figure 4.2.1.3 depicts the rolling 5 year ex-post volatility of the portfolios over time.

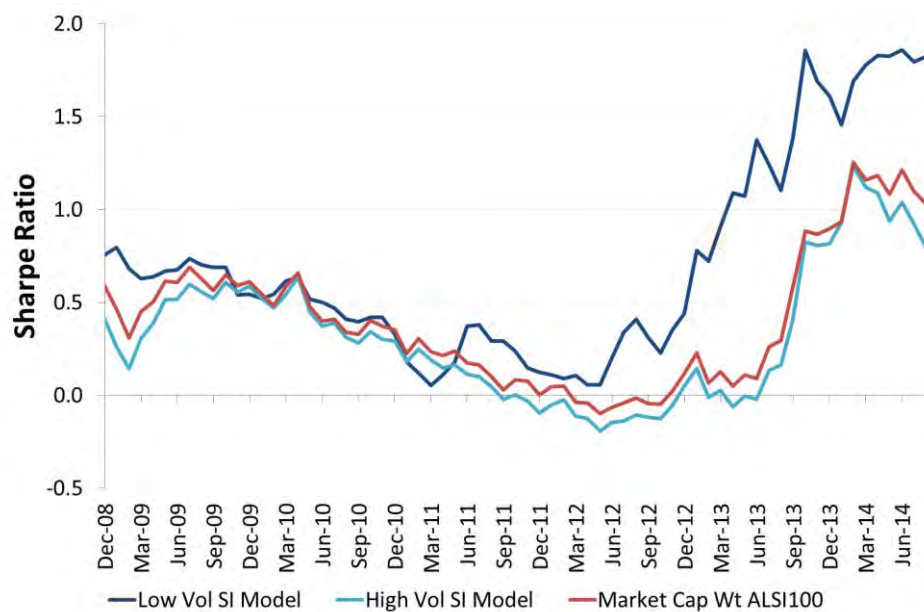
**Figure 4.2.1.3: Rolling 5 Year Ex-Post Volatility of the portfolios constructed using Top 100 JSE shares over time**



From Figure 4.2.1.3 it is evident that the low volatility portfolio consistently had lower risk than the high volatility and market-cap weighted portfolios out-of-period on a rolling 5 year basis. From Figure 4.2.1.2 and Figure 4.2.1.3; in the South African market the low volatility portfolio has been found to outperform the high volatility portfolio while preserving its low volatility characteristics out-of-period, consistent with international studies which have been cited already.

In Figure 4.2.1.4 below the rolling 5 year Sharpe ratios of the portfolios are depicted.

**Figure 4.2.1.4: Rolling 5 Year Sharpe ratios of the portfolios constructed using Top 100 JSE shares over time**



The low volatility (Figure 4.2.1.3) has been accompanied by a predominantly higher Sharpe ratio for the low volatility portfolio relative to the high volatility and market-cap weighted portfolios over time. However, it is important to note that the Sharpe ratio has not always been higher for the low volatility portfolio as it has produced lower Sharpe ratios during times when the performance (Figure 4.3.1.2) has lagged the market-cap weighted and high volatility portfolios.

***Determining if the observed low volatility outperformance (relative to market-cap weighted and high volatility portfolios) is attributable to a sector bias effect***

Given that the aim of this thesis is to understand if the outperformance is a result of a low beta effect or rather a sector effect, Table 4.2.1.2 below depicts the average sector weightings within the low volatility and high volatility portfolios over the period December 2003 to August 2014. This analysis is expected to show if there is a sector bias within the portfolios; for example it would show if there is a sector that the one methodology has preferred relative the other which could have resulted in the outperformance.

**Table 4.2.1.2: Average Sector allocations in the portfolio (Dec 2003 – Aug 2014)**

Sector	Low Vol SI Model	High Vol SI Model	Market Cap Wt ALSI100
Resources	0%	42%	39%
Financials	58%	22%	20%
Listed Property	41%	1%	3%
Industrials	42%	36%	41%

From Table 4.2.1.2 it is evident that the low volatility portfolio has been significantly overweight the Listed Property sector relative to the ALSI 100. On average the low volatility portfolio has a weight of 41% in this sector while the ALSI 100 only has 3% (later it will be shown that the Listed Property sector has a very low beta relative to the market-cap weighted ALSI). On the contrary the allocation to Listed Property in the high volatility portfolio has been similar to that of the ALSI 100 (i.e. an average of 1% in the high volatility portfolio). One could argue that the observed outperformance is more of a sector effect rather than a low beta effect.

Figure 4.2.1.5 below depicts the performance of the Listed Property sector relative to the JSE All Share index (ALSI) over the back-test period (i.e. December 2003 – August 2014).

**Figure 4.2.1.5: Performance of Listed Property vs. the JSE All Share Index**



Given that Listed Property has outperformed the ALSI as shown in Figure 4.2.1.5 this could skew the interpretation of the outperformance observed in the low volatility portfolio. Given that the low volatility portfolio has been considerably overweight the Listed Property sector as shown in Table 4.2.1.2; the observed outperformance could be a result of the overweight Property position relative to the high volatility and market-cap weighted portfolios as opposed to a low beta effect.



After back-testing the low risk anomaly in the U.S. market; Baker *et al.* (2014) decompose the anomaly into its micro and macro components. The macro component comes from selecting low beta industries or countries; while the micro component comes from selecting low beta stocks within industries or countries. The appealing feature of this methodology is that it enables one to investigate how much of the low beta anomaly comes from industry selection and how much comes from selecting low beta stocks within industries or countries. In this case this should help determine how much of the outperformance can be attributed to the Property and FINDI vs. RESI sector effects. In the U.S. market they found the low beta anomaly to not be statistically significant at the sector level. However, they found the low beta anomaly to be statistically significant at stock selection level within industries. From this it is concluded that in the U.S. market the low beta anomaly is not a result of an industry selection effect but rather a result of selecting low beta stocks within industries. In other words, Baker *et al.* (2014) found the low volatility anomaly to be attributable to a stock selection effect rather than an industry effect.

In this thesis a statistical test is performed in the South African market to determine if the anomaly is attributable to low beta stock selection or rather a sector selection effect, similar to Baker *et al.* (2014). The potential sector selection effects that could bias the anomaly in the South African market are highlighted in Table 4.2.1.2. From this it is evident that the low volatility portfolio is overweight Listed Property shares relative to the high volatility portfolio. Secondly, the low volatility portfolio is underweight the Resources sector (RESI) and overweight the Financial and Industrial (FINDI) sectors relative to the high volatility portfolio. To test for potential sector biases in the results, the methodology of Baker *et al.* (2014) was adapted in the South African market as formulated in the regression analysis below:

$$R_{lowV,t} - R_{highV,t} = \alpha + \beta(R_{Prop,t} - R_{mkt,t}) + \gamma(R_{FINDI,t} - R_{RESI,t}) \quad (10)$$

where  $R_{lowV,t}$  = return of *low volatility* portfolio at time  $t$

$R_{highV,t}$  = return of *high volatility* portfolio at time  $t$

$R_{Prop,t}$  = return of *SA Listed Property* at time  $t$

$R_{mkt,t}$  = return of *JSE All Share* index at time  $t$

$R_{FINDI,t}$  = return of the *JSE Financial & Industrial 25* index at time  $t$

$R_{RESI,t}$  = return of the *JSE Resources 10* index at time  $t$

**Table 4.2.1.3: Regression Results using ALSI 100 universe (December 2003 – August 2014)**

<i>Regression Statistics</i>	
Multiple R	89%
R Square	80%
Adjusted R Square	79%
Standard Error	2.14
Observations	128

ANOVA					
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	2	2 257.17	1 128.59	245.52	0%
Residual	125	574.60	4.60		
Total	127	2 831.77			

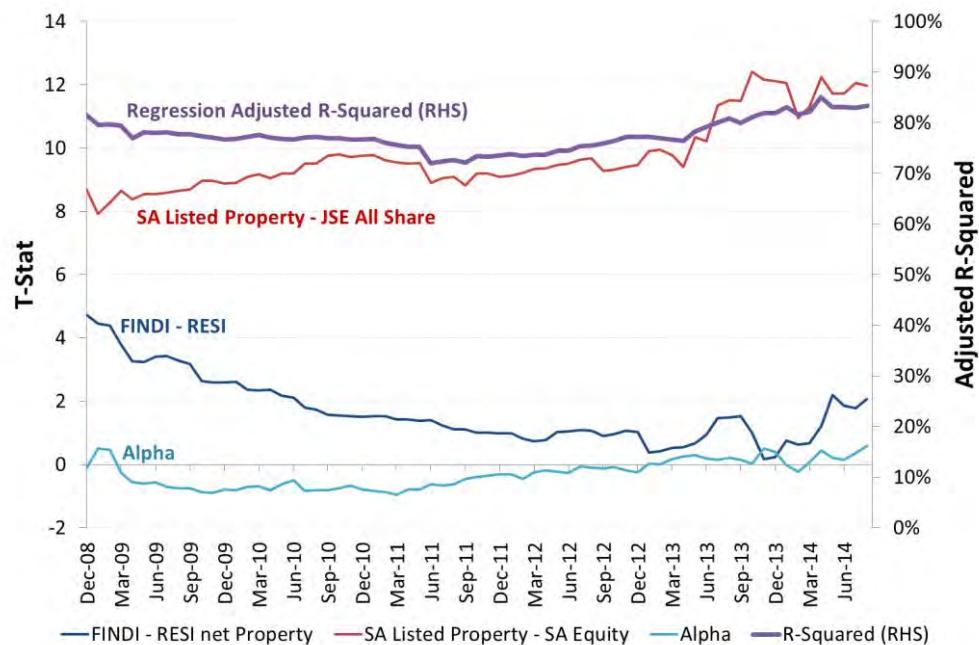
  

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Alpha	-0.05	0.19	-0.28	78%	-0.43	0.32	-0.43	0.32
FINDI - RESI net Property	0.17	0.04	4.28	0%	0.09	0.25	0.09	0.25
SA Listed Property - SA Equity	0.61	0.04	14.23	0%	0.53	0.70	0.53	0.70

The variation in the outperformance (of the low volatility over the high volatility portfolio) explained by the Listed Property and FINDI vs. RESI sector effects is 79% as shown by the adjusted R-squared in Table 4.2.1.3. The F-statistic has a p-value of 0% implying that at least one of the independent variables is a significant explanatory variable. In addition it can be concluded from the significance of the F-statistic that the relationship between the independent variables and the response variable is statistically significant. From the above ANOVA table, the t-statistics for both independent variables are significant (i.e. 14.2 and 4.3) suggesting that both these variables are significant at explaining the outperformance of the low volatility portfolio. This can also be witnessed by the low p-values of 0.0% for both the Listed Property and FINDI-RESI sector effects. All else equal a 1.0% outperformance from Listed Property would lead to a 0.6% outperformance of the low volatility portfolio. Similarly, a 1% outperformance of the FINDI over the RESI would lead to a 0.2% outperformance of the low volatility portfolio relative to high volatility portfolio, all else equal. Having taken into account the sector effects, the low volatility portfolio does not have a significant alpha relative to the high volatility portfolio over the back-test period. The alpha of -0.05 has a t-statistic of -0.28 and a poor p-value of 78.4%. At face value this evidence would suggest that, in the South African market the low volatility anomaly can be attributed to a Listed Property and FINDI vs. RESI sector effect over the period December 2003 to August 2014 as opposed to a low volatility alpha.

To establish if the above findings have held consistently over time the regression analysis in equation (10) is performed on a rolling 5 year basis. The t-statistics of the regression coefficients and the adjusted R-squared are depicted in Figure 4.2.1.6.

**Figure 4.2.1.6: Rolling 5 Year T-statistic and R-Squared of Relative Return**

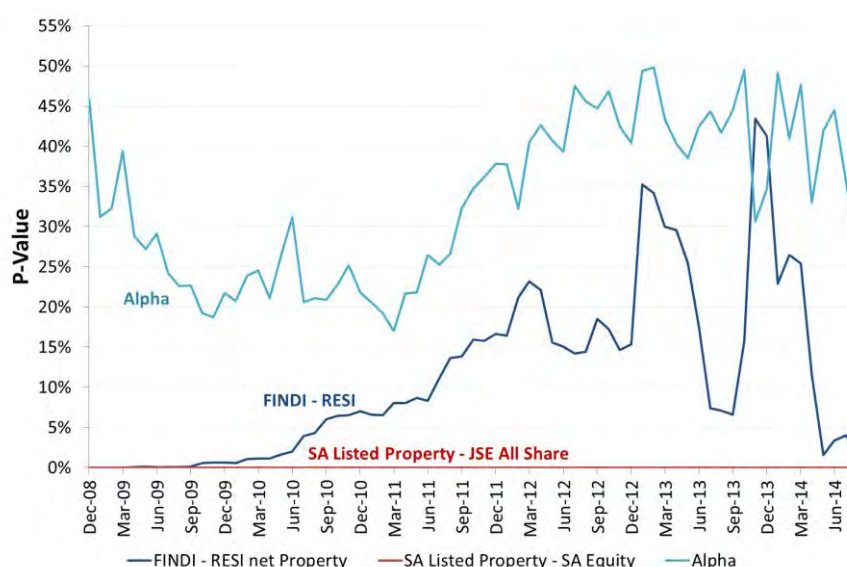


From Figure 4.2.1.6 the regression analysis (equation (10)) has explained more than 70% of the variation in outperformance of the low volatility portfolio relative to the high volatility portfolio over time as shown by the adjusted R-squared. From this it can be concluded that the independent variables explain most of the variation in outperformance of the low volatility portfolio over the high volatility portfolio.

The rolling t-statistic of the relative performance of Listed Property (relative to the JSE All Share index) has been 8.0 or above. As expected, this implies that there is a significant positive linear relationship between the outperformance of the low volatility over the high volatility portfolio and the outperformance of the Listed Property sector. Over the entire back-test period the t-statistic for the FINDI-RESI was 4.28 indicating a strong positive relationship. However, it can be noted from Figure 4.2.1.6 that this relationship has not held consistently over time. The t-statistic for this variable has been fairly low over time, in most cases it has been below 2.0. Consistent with Table 4.2.1.3 the t-statistic for alpha, holding the Listed Property and FINDI vs. RESI sector effect constant, has been close to zero over time.

Figure 4.2.1.7 below depicts the p-values of the t-statistics shown in Figure 4.2.1.6 over time.

**Figure 4.2.1.7: P-Values of the rolling 5 year regression t-statistics**



On a 5 year rolling basis the p-value for the Listed Property sector outperformance (relative to the JSE All Share) has been almost 0.0% consistently. As such this confirms that the Listed Property sector outperformance explains a significant part of the outperformance of the low volatility relative to the high volatility portfolio. However, the same cannot be said of the p-value of the FINDI-RESI sector effect which has predominantly been above 10%. In addition, the p-value for the FINDI-RESI sector effect has been very volatile on a rolling 5 year basis. Given the rolling p-values for this sector effect; one cannot conclude that there is a significant linear relationship between the FINDI-RESI sector outperformance and the outperformance of the low volatility portfolio over the high volatility portfolio holding the relative performance of the Listed Property sector constant.

Holding the FINDI-RESI and Listed Property relative performance constant, one cannot conclude that the low volatility portfolio has a statistically significant alpha relative to the high volatility portfolio. The t-statistic for the alpha has consistently been close to zero over time and the p-value has been 15% or worse.

Based on this analysis the logical conclusion that follows is that the outperformance of the low volatility portfolio over the high volatility portfolio can be primarily attributed to the overweight Listed Property sector. In other words the outperformance could have been as a result of the asset allocation decision (i.e. overweight Property) as opposed to a low beta outperformance.

One of the assumptions of multivariate regression is that of no multi-collinearity. This problem arises if the independent variables are correlated. The problem with multi-collinearity, as shown by Vasu and Elmore (1975), is that it results in large standard errors and subsequently low t-statistics. As such, it increases the probability of committing a type II error where one erroneously fails to reject a false null hypothesis. This implies that one is

more likely to erroneously fail to detect a relationship that truly exists between the dependent and independent variables.

To test if there is a linear relationship between the explanatory variables the following regression analysis is performed:

$$R_{FINDI,t} - R_{RESI,t} = \beta * (R_{Prop,t} - R_{mkt,t}) + \alpha \quad (11)$$

where the *variables* are as *defined* in equation (10)

**Table 4.2.1.4: ANOVA table obtained from regression of FINDI-RESI relative to Listed Property (Dec 2003 – Aug 2014)**

Regression Statistics	
Multiple R	63%
R Square	39%
Adjusted R Square	39%
Standard Error	4.82
Observations	128.00

ANOVA					
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	1	1 904.03	1 904.03	82.11	0%
Residual	126	2 921.92	23.19		
Total	127	4 825.95			

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	0.42	0.43	0.99	33%	-0.42	1.26	-0.42	1.26
SA Listed Property - SA Equity	0.68	0.08	9.06	0%	0.53	0.83	0.53	0.83

From Table 4.2.1.4 there is a statistically significant positive linear relationship between the Listed Property outperformance over the JSE ALSI and FINDI – RESI outperformance as shown by the p-value of 0%. For every 1% outperformance from the Listed Property sector (relative to the Equity market), the FINDI is expected to outperform the RESI sector by 0.68% all else equal. Given the statistically significant F-statistic, with a p-value of 0%, it can be concluded that the regression is statistically significant and the results are reliable. This linear relationship between the independent variables of equation (10) may distort the analysis given the significant correlation between them.

Given the potential multi-collinearity problem inherent in the regression in (10), an alternative methodology is used to test the explanatory power of the Listed Property and FINDI vs. RESI sector effects. This methodology was introduced by Xiong, Ibbotson, Idzorek and Chen (2010) who decomposed the performance of a balanced portfolio into the following components: strategic asset allocation, tactical asset allocation and stock selection. The final aim of their research was to show how the overall performance of a balanced fund can be decomposed into these components. Adapting their approach into this low volatility vs. high volatility setting one can decompose the relative return of the low volatility vs. high volatility portfolio as follows:

low volatility outperformance

= Property outperformance

+ FINDI Outperformance net the Property effect

+ low volatility alpha net of the FINDI vs RESI sector effect

$$\begin{aligned}
 R_{lowV,t} - R_{highV,t} &= (R_{Prop,t} - R_{mkt,t}) + \{(R_{FINDI,t} - R_{RESI,t}) - (R_{Prop,t} - R_{mkt,t})\} \\
 &+ \{R_{lowV,t} - R_{highV,t} - (R_{FINDI,t} - R_{RESI,t})\} \quad (12)
 \end{aligned}$$

where  $R_{lowV,t}$  = return of *low volatility* portfolio at time  $t$

$R_{highV,t}$  = return of *high volatility* portfolio at time  $t$

$R_{Prop,t}$  = return of *SA Listed Property* at time  $t$

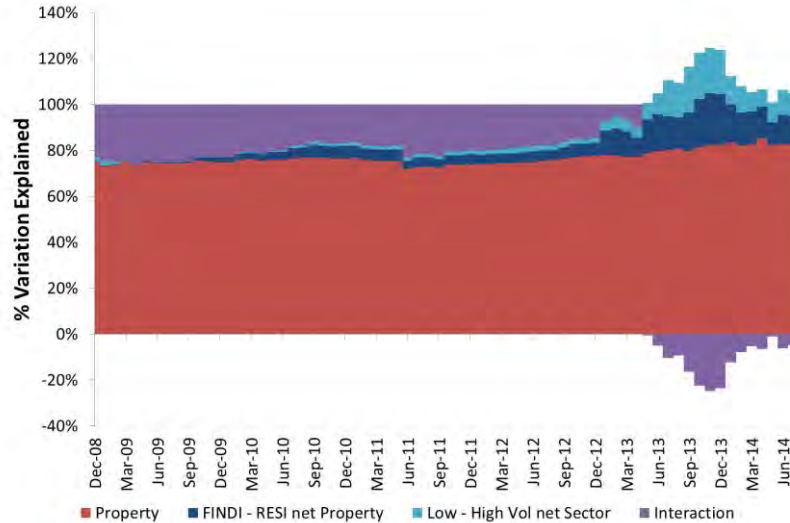
$R_{mkt,t}$  = return of *JSE All Share* index at time  $t$

$R_{FINDI,t}$  = return of the *JSE Financial & Industrial 25* index at time  $t$

$R_{RESI,t}$  = return of the *JSE Resources 10* index at time  $t$

Xiong *et al.* (2010) then perform a regression of the individual components on the right hand side of equation (12) against the relative performance. The R-squared obtained from the individual components in this derivation then show the variation in outperformance explained by these components.

**Figure 4.2.1.8: Variation in outperformance explained by sector effect vs. low beta effect**



From Figure 4.2.1.8 it is evident that the majority of the variation in outperformance can be explained by the Property sector effect. This component explains more than 80% of the variation in outperformance, consistent with the finding from the regression in (10). While the variation explained by the FINDI – RESI sector effect (net of Property) has increased recently, it still explains a very low proportion of the variation in the low volatility outperformance over the high volatility portfolio. The remaining low beta vs. high beta alpha (net of the sector effects) has explained a very low proportion of the variation in the low volatility outperformance over the high volatility portfolio over time. From Figure

4.2.1.8 it can be concluded that the majority of the variation in the low volatility outperformance over the high volatility portfolio can be attributed to a Property sector effect.

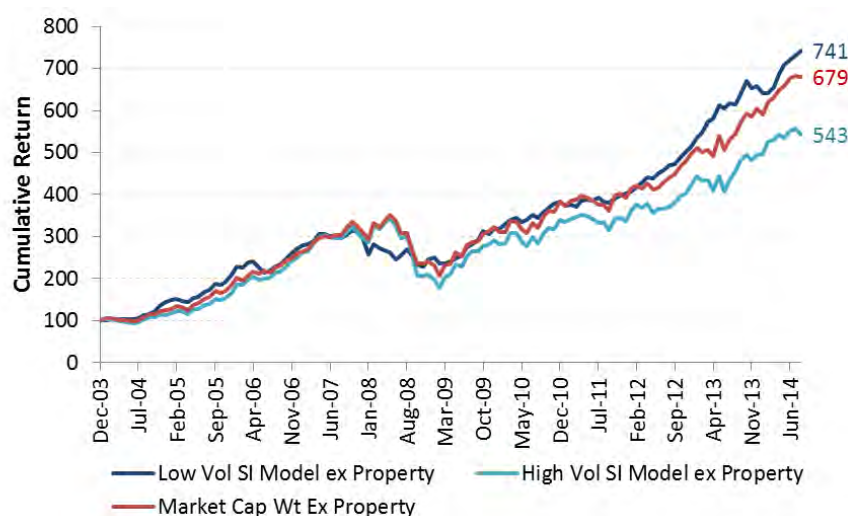
The evidence from the statistical tests performed thus far suggests that the low volatility effect can be attributed to a Listed Property sector effect in the South African market; and is not widespread across the sectors. If that is the case then one would expect the low volatility outperformance to disappear if the Listed Property sector effect is neutralised or excluded. To test empirically if the outperformance (i.e. low volatility vs. high volatility) can be attributed to a Property sector effect alone, Property stocks will be excluded from the investable universe and the back-test will be re-run. If the outperformance disappears it can then be concluded that in the South African setting; the low volatility outperformance relative to the high volatility portfolio has just been a by-product of a Property sector effect.

#### 4.2.2. Back-test results using Top 100 JSE shares excluding Property stocks

Figure 4.2.2.1 depicts the cumulative total returns of R100 invested in the low volatility, high volatility and market-cap weighted portfolios as at 31 December 2003 to 31 August 2014. On the figure the following abbreviations have been used:

- Low Vol SI Model ex Property (Clarke *et al.* (2011) minimum variance portfolio constructed using JSE largest 100 shares excluding Property shares)
- High Vol SI Model ex Property (high volatility portfolio created using a derivation similar to Clarke *et al.* (2011) using JSE largest 100 shares excluding Property shares)
- Market-cap Wt ex Property (market-cap weighted portfolio of the largest 100 JSE shares excluding Property shares – for consistency in comparisons)

**Figure 4.2.2.1: Cumulative Returns constructed using Top 100 JSE shares excluding Property**





After Property shares are excluded from the investable universe the performance of the low volatility portfolio has marginally worsened (i.e. 796 in Figure 4.2.1.1 vs. 741 in Figure 4.2.2.1). However, this portfolio has still outperformed both the high volatility and market-cap weighted portfolios (all excluding Property shares). This would then suggest that there is more to the low volatility outperformance than just a Property sector effect.

To test the statistical significance of the outperformance the market model regression, as was formulated in equation (9) is performed on the monthly returns of the portfolios. This will help establish if the low volatility portfolio has a significant positive alpha relative to the high volatility portfolio out-of-period, after excluding Property stocks from the investable universe.

Table 4.2.2.1 below shows the ANOVA table obtained from the market model regression.

**Table 4.2.2.1: ANOVA table obtained from Low – High Vol portfolio market model regression (December 2003 – August 2014)**

<i>Regression Statistics</i>	
Multiple R	64%
R Square	41%
Adjusted R Square	40%
Standard Error	3.11
Observations	128

ANOVA					
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	1	833.90	833.90	86.22	0%
Residual	126	1 218.67	9.67		
Total	127	2 052.57			

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
<b>Net Alpha (Low - High Vol)</b>	0.73	0.28	2.59	1%	0.17	1.29	0.17	1.29
<b>Net Beta (Low - High Vol)</b>	-0.54	0.06	-9.29	0%	-0.66	-0.43	-0.66	-0.43

The above market model regression has an R-squared of 41% and a significant F-statistic as shown by the p-value of 0%. As such, it can be concluded that the market model regression is statistically significant. After excluding Property stocks from the investable universe, the beta of the low volatility portfolio is statistically significantly less than that of the high volatility portfolio by 0.54 as shown by the p-value of 0%; out-of-period. In addition, the low volatility portfolio has a statistically significant positive alpha of 0.73% (out-of-period) relative to the high volatility portfolio as depicted by the p-value of 1%. Thus, contrary to the finding in the previous section; it can be concluded from empirical and statistical tests that the low volatility outperformance relative to the high volatility portfolio is prevalent even after the exclusion of the Property sector effect in the South African market.

Figure 4.2.2.2 depicts the rolling 5 year returns of the low volatility, high volatility and market-cap weighted portfolios. This will help establish if the outperformance has been achieved consistently over time.



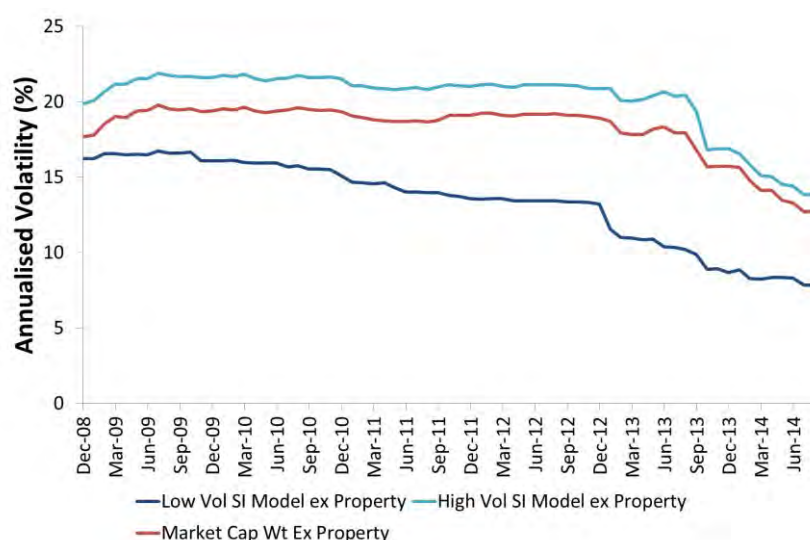
**Figure 4.2.2.2: Rolling 5 Year Returns using Top 100 JSE shares excluding Property**



From Figure 4.2.2.2 the low volatility portfolio has outperformed the high volatility portfolio 67% of the time, while also outperforming the market-cap weighted portfolio 57% of the time on a rolling 5 year basis. While these incidences of outperformance are lower than the case where Property stocks are included in the analysis, they are still meaningful and imply superior performance from the low volatility portfolio.

Figure 4.2.2.3 below depicts the rolling 5 year ex-post risk of the low volatility, high volatility and market-cap weighted portfolios over time, where the investable universe excludes Property stocks.

**Figure 4.2.2.3: Rolling 5 Year Volatility of the portfolios constructed using Top 100 JSE shares excluding Property shares**

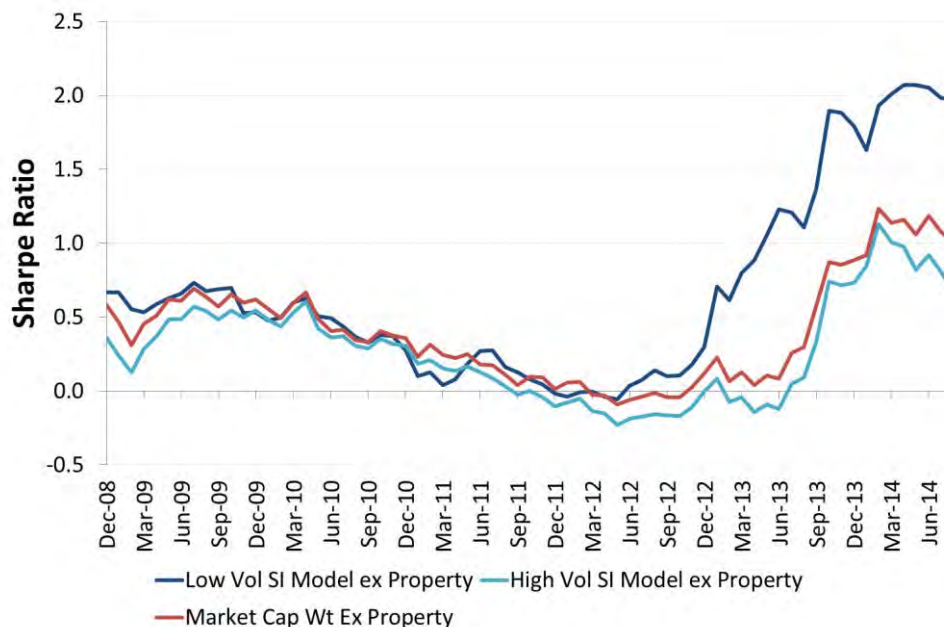


From Figure 4.2.2.3 it is evident that the low volatility portfolio has retained its risk characteristics out-of-period. This portfolio has consistently had significantly lower risk than both the market-cap weighted and high volatility portfolios over time, highlighting that the

low volatility findings in the South African setting have been consistent with the findings in other international markets.

Figure 4.2.2.4 below depicts the rolling 5 year Sharpe ratios of the portfolios over time.

**Figure 4.2.2.4: Rolling 5 Year Sharpe ratios of the portfolios constructed using Top 100 JSE shares excluding Property shares**



After the exclusion of Property shares from the investable universe, the low volatility portfolio has still predominantly produced a higher Sharpe ratio than both the market-cap weighted and high volatility portfolios over time. This suggests that the risk-return characteristics of the low vs. high volatility portfolios cannot be attributed to only a Property sector effect as the findings are similar before and after the exclusion of Property stocks.

***Determining if the observed low volatility outperformance (relative to market-cap weighted and high volatility portfolios) is attributable to a sector bias effect***

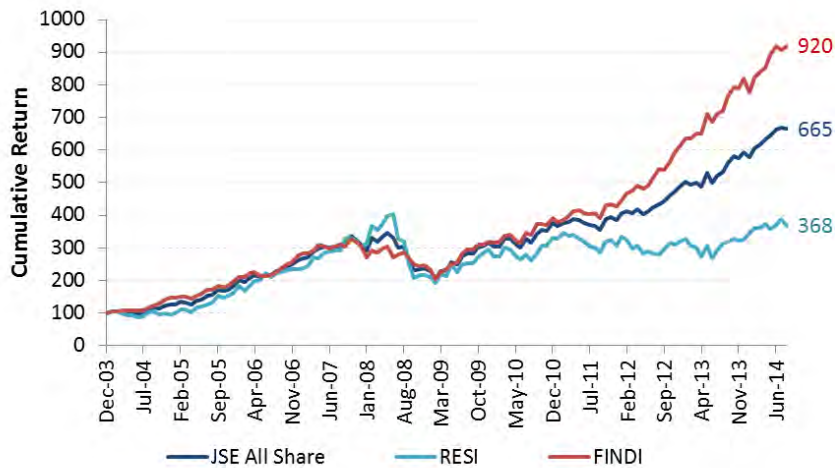
Again it is important to analyse the sector decomposition within the portfolios over time to gauge if there is a sector that has been significantly overweighted. This would help one understand if the outperformance observed is a result of a sector bias or if it is in fact a low volatility anomaly.

**Table 4.2.2.2: Sector allocation in the portfolios (Dec 2003 – Aug 2014)**

Sector	Low Vol SI Model ex Property	High Vol SI Model ex Property	Market Cap Wt ex Property
Resources	4%	42%	40%
Financials	27%	21%	18%
Industrials	69%	38%	43%

From Table 4.2.2.2 it is evident that the low volatility portfolio has been significantly overweight Industrials and Financial stocks relative to the high volatility and market-cap weighted portfolios. On average the low volatility portfolio has been 38% underweight Resources relative to the high volatility portfolio. One can argue that the outperformance of the low volatility portfolio could just be a sector effect as opposed to a low beta effect given that the FINDI has materially outperformed the RESI over this period as depicted in Figure 4.2.2.5 below.

**Figure 4.2.2.5: Cumulative Returns of RESI and FINDI vs. JSE All Share index**



A regression analysis similar to Baker *et al.* (2014) is performed to help disentangle if the outperformance can be attributed to a sector effect (i.e. overweight FINDI vs. RESI). The formulation used is as follows:

$$R_{low_{exProp},t} - R_{high_{exProp},t} = \alpha + \gamma(R_{FINDI,t} - R_{RESI,t}) \quad (13)$$

where  $R_{low_{exProp},t}$  = return of *low volatility* portfolio (excl. Property) at time  $t$

$R_{high_{exProp},t}$  = return of *high volatility* portfolio (excl. Property) at time  $t$

$R_{FINDI,t}$  = return of the *JSE Financial & Industrial 25* index at time  $t$

$R_{RESI,t}$  = return of the *JSE Resources 10* index at time  $t$

**Table 4.2.2.3: Regression Results excluding Property stocks (December 2003 – August 2014)**

Regression Statistics	
Multiple R	67%
R Square	45%
Adjusted R Square	44%
Standard Error	3.01
Observations	128.00

ANOVA					
	df	SS	MS	F	Significance F
Regression	1	914.69	914.69	101.29	0%
Residual	126	1 137.88	9.03		
Total	127	2 052.57			

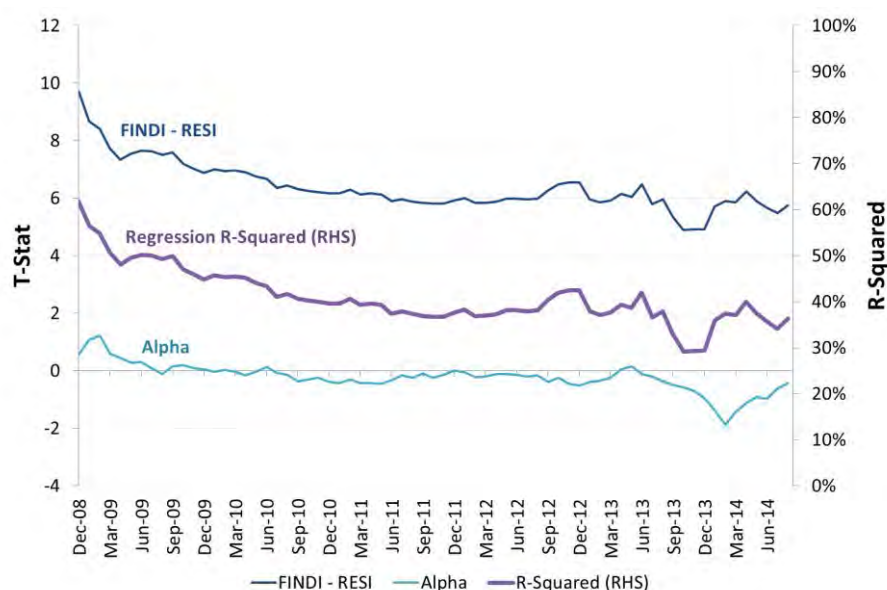
  

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Alpha	-0.07	0.27	-0.27	79%	-0.60	0.46	-0.60	0.46
FINDI - RESI	0.44	0.04	10.06	0%	0.35	0.52	0.35	0.52

The R-squared from the above regression is 45% and the F-statistic is significant with a p-value of 0%. While it can be concluded that the regression is statistically significant, there is still a significant proportion of the variation (i.e. more than 50%) in outperformance that remains unexplained. The FINDI vs. RESI sector effect is a statistically significant explanatory variable with a t-statistic of 10.1 and a p-value of 0%. The average outperformance, net of the FINDI – RESI sector effect, is -0.1% as shown by the intercept coefficient in Table 4.2.2.1. However the p-value of this coefficient is 79%, implying that it cannot be concluded the average outperformance (net of the FINDI vs. RESI sector effect) is statistically significantly different from zero.

In Figure 4.2.2.6 this relationship is tested on a rolling 5 year basis over time to determine if it has held consistently over time.

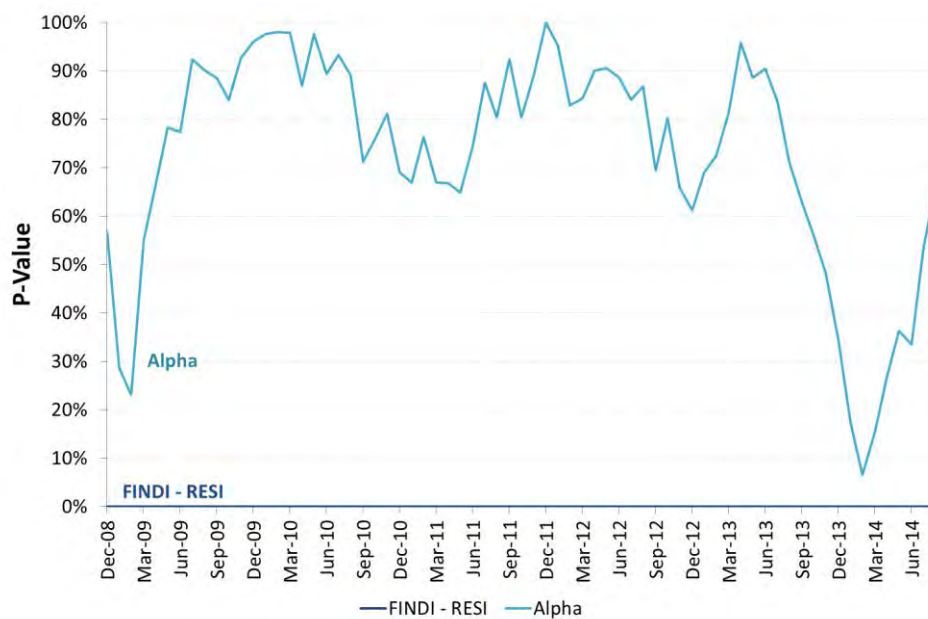
**Figure 4.2.2.6: Rolling 5 Year T-statistic and R-Squared of Regression**



From Figure 4.2.2.6 the FINDI-RESI relative performance is a significant explanatory variable of the outperformance of the low volatility relative to the high volatility portfolio, with the t-statistic consistently above 4.0. However, this variable has predominantly explained less than 50% of the variation in outperformance over time. Thus, there is still a significant proportion of the variation (i.e. more than 50%) in the low volatility portfolio outperformance over the high volatility portfolio that remains unexplained.

Figure 4.2.2.7 depicts the p-values of the regression variables.

**Figure 4.2.2.7: Rolling 5 year P-Values of the regression**



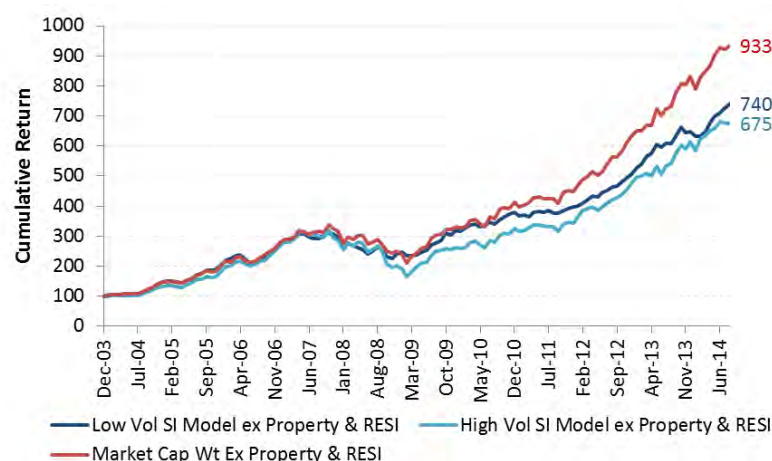
The FINDI-RESI sector effect has been a significant explanatory variable with a p-value consistently close to zero over time. On the other hand the low volatility alpha net of the FINDI-RESI sector effect has not been significant over time. From Figure 4.2.2.6 and Figure 4.2.2.7 above it can be concluded the FINDI vs. RESI sector effect explains a statistically significant portion of the low volatility effect in the South African market. To test if the low volatility anomaly exists after the exclusion of the Listed Property and FINDI vs. RESI shares in the South African market; the back-test will be re-run excluding the Listed Property and RESI shares from the investable universe. This back-test will reveal if the outperformance of the low volatility portfolio (relative to the high volatility portfolio) is still prevalent after excluding the Property and FINDI vs. RESI sector effects. If the low volatility portfolio outperformance over the high volatility portfolio suddenly disappears after the neutralisation of these sector effects, it can then be concluded that the low volatility effect has been as a result of the Listed Property and FINDI vs. RESI sector effects in the South African market.

#### 4.2.3. Back-test results using Top 100 JSE shares excluding Property & RESI stocks

Figure 4.2.3.1 depicts the cumulative total returns of R100 invested in the low volatility, high volatility and market-cap weighted portfolios as at 31 December 2003 to 31 August 2014. On the figure the following abbreviations have been used:

- Low Vol SI Model ex Property & RESI (Clarke *et al.* (2011) minimum variance portfolio constructed using JSE largest 100 shares excluding Property & RESI shares)
- High Vol SI Model ex Property & RESI (high volatility portfolio created using a derivation similar to Clarke *et al.* (2011) using JSE largest 100 shares excluding Property & RESI shares)
- Market-cap Wt ex Property & RESI (market-cap weighted portfolio of the largest 100 JSE shares excluding Property & RESI shares)

**Figure 4.2.3.1: Cumulative Returns using Top 100 shares excluding Property & RESI**



From Figure 4.2.3.1 it is evident that both the low volatility and high volatility portfolios have underperformed the market-cap weighted portfolio. This could suggest that the outperformance of the prior low volatility portfolios achieved over the market-cap weighted portfolios may have been as a result of the underweight Resources sector position. Yamada and Nagawatari (2010) argue that the price volatility of a stock should reflect the underlying expected earnings variability. As such the sector over/ underweight position would be driven by the underlying sector expected earnings variability. This would imply that sectors with low or high variability in their earnings would, by construction, have overweight positions in the low or high volatility portfolios respectively. The exclusion of sectors that the low or high volatility portfolios would have invested in, forces these portfolios into sectors they otherwise would not have invested in. As such this may distort the resultant portfolio characteristics after the imposition of sector constraints. This potential distortion of the portfolio characteristics may be material and may explain the underperformance of



the low volatility portfolio relative to the market-cap weighted portfolio. Later in this chapter the impact of the imposition of these sector constraints on the portfolios will be analysed in detail.

More importantly the outperformance of the low volatility portfolio over the high volatility portfolio has still been prevalent, even after excluding both the Property and RESI vs. FINDI sector effects. This is consistent with international literature (see Baker *et al.* (2011), Baker & Haugen (2012) among others) which noted the low volatility anomaly as the outperformance of the low volatility portfolios relative to the high volatility portfolios. The above finding suggests that there is more to the outperformance of the low volatility portfolio over the high volatility portfolio than just a sector effect. Importantly, this finding is consistent with the findings from the statistical tests performed earlier in this chapter (i.e. excluding Property shares from investable universe) and Baker *et al.* (2011) who also concluded that the low volatility effect (i.e. low volatility outperformance relative to high volatility) cannot be attributable to just an industry or country effect. In fact they found the anomaly to be more pronounced at the stock selection level within industries or within countries.

In Table 4.2.3.1 below the statistical significance of this outperformance is tested using the market model regression as was defined in equation (9). The aim of this regression is to determine if the low volatility portfolio has a statistically significant positive alpha relative to the high volatility portfolio out-of-period, after excluding Property and Resources shares.

**Table 4.2.3.1: ANOVA table obtained from Low – High Vol portfolio market model regression (December 2003 – August 2014)**

Regression Statistics	
Multiple R	50%
R Square	25%
Adjusted R Square	25%
Standard Error	2.66
Observations	128

ANOVA					
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	1	299.83	299.83	42.36	0%
Residual	126	891.93	7.08		
Total	127	1 191.75			

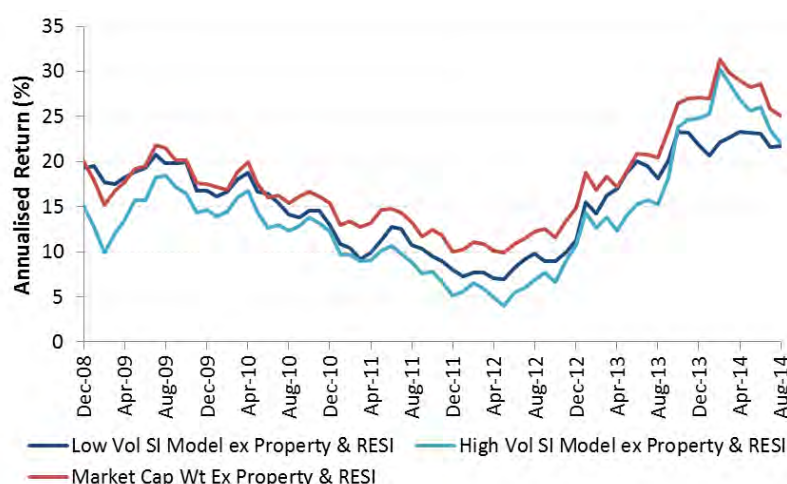
	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
<b>Net Alpha (Low - High Vol)</b>	0.47	0.24	1.92	6%	-0.01	0.96	-0.01	0.96
<b>Net Beta (Low - High Vol)</b>	-0.36	0.05	-6.51	0%	-0.46	-0.25	-0.46	-0.25

The market model regression in Table 4.2.3.1 has explained 25% of the variation in the low volatility outperformance relative to the high volatility portfolio. While this R-squared is low, the statistically significant F-statistic with a p-value of 0% implies that the regression is statistically significant. After excluding the Property and RESI shares from the investable universe, the beta of the low volatility portfolio is statistically significantly (p-value of 0%) less than that of the high beta portfolio by 0.36, out-of-period. The low volatility portfolio

has a positive alpha of 0.47% relative to the high volatility portfolio and this has a p-value of 6%. Thus, we conclude that the low volatility portfolio has a positive alpha relative to the high volatility portfolio of 0.47% with a probability of 94%. From the above results it can be concluded that the low volatility portfolio has consistently had a positive alpha relative to the high volatility portfolio whether the Property and RESI shares are included or excluded from the investable universe. These results would suggest that the ex-post security market line is flatter than is implied by the CAPM. These findings in the South African setting are consistent with those in international literature (see Baker *et al.* (2014), Baker & Haugen (2012), Hsu *et al.* (2013) among others).

To investigate if this outperformance has just been a one-off or if it has been achieved consistently over time, Figure 4.2.3.2 below depicts the rolling 5 year returns of the portfolios.

**Figure 4.2.3.2: Rolling 5 Year Returns using Top 100 shares excluding Property & RESI**



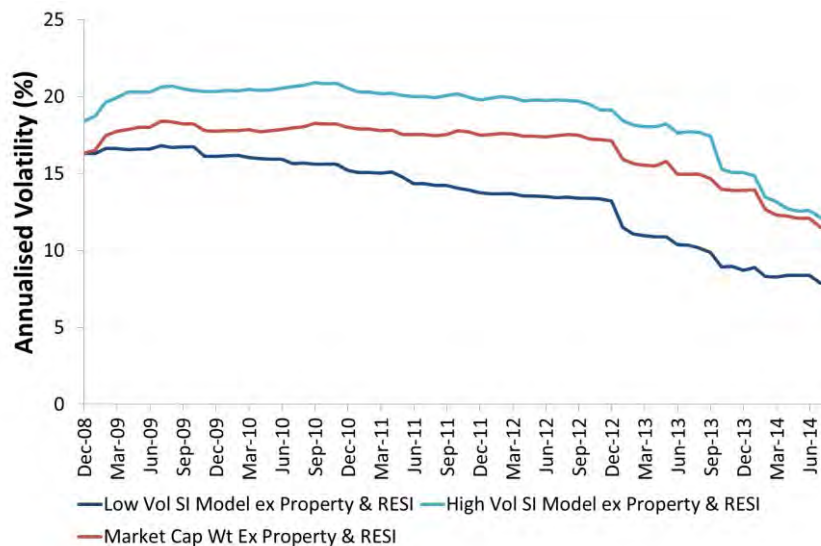
From 3.2.15 it is evident that both the low volatility and high volatility portfolios have underperformed the market-cap weighted portfolio fairly consistently over time. An in-depth analysis of the potential causes of this underperformance will be performed later in this chapter.

On the other hand, the low volatility portfolio has outperformed the high volatility portfolio fairly consistently on a rolling 5 year basis. The low volatility portfolio has outperformed the high volatility portfolio 84% of the time on a rolling 5 year basis, suggesting strong and consistent outperformance. Given that this outperformance has been achieved after taking into account the sector effects, it would suggest that it is not just as a result of a sector bias. In fact it can be concluded that in the South African market the low beta anomaly is prevalent at the stock selection level, consistent with Baker *et al.* (2014). On the other hand this finding would also support the findings of Black (1972) that the security market line is flatter than that implied by the CAPM.



Figure 4.2.3.3 below depicts the rolling 5 year ex-post volatility of the portfolios over time. This will show if the risk characteristics have been preserved out-of-period after excluding the Property and RESI stocks from the investable universe.

**Figure 4.2.3.3: Rolling 5 Year Volatility of the portfolios constructed using the Top 100 JSE shares excluding Property and RESI stocks**



Consistent with the previous findings and international literature the low volatility and high volatility portfolios have preserved their risk characteristics out-of-period. Thus, it can be concluded that in the South African market the low volatility portfolio has outperformed the high volatility portfolio at a significantly lower risk out-of-period even after taking into account the Property and RESI vs. FINDI sector effects.

Figure 4.2.3.4 below depicts the rolling 5 year Sharpe ratios of the portfolios over time.

**Figure 4.2.3.4: Rolling 5 Year Sharpe ratios of the portfolios constructed using the Top 100 JSE shares excluding Property and RESI stocks**



The exclusion of Property and Resources stocks from the investable universe has resulted in increased Sharpe ratios for the market-cap weighted and high volatility portfolios. The inclusion of these sector constraints has resulted in the market-cap weighted portfolio producing a predominantly higher Sharpe ratio than both the low volatility and high volatility portfolios over time. This highlights the change in the risk-return portfolio characteristics that have been brought about by the sector constraints. On the other hand it is evident from Figure 4.2.3.4 that the low volatility portfolio has consistently had a higher Sharpe ratio than the high volatility portfolio in the South African environment, consistent with international literature.

***Determining if the observed low volatility outperformance (relative to the high volatility portfolio) is attributable to a sector bias effect***

After taking into account the FINDI vs. RESI sector effect, Table 4.2.3.2 investigates if there has been a prevalent sector effect within FINDI. This will help establish if the portfolios have had a certain preference for particular sectors which could have inherently caused the out/underperformance.

**Table 4.2.3.2 Average Sector Weights within the portfolios (December 2003 – August 2014)**

Sector	Low Vol SI Model ex Property & RESI	High Vol SI Model ex Property & RESI	Market Cap Wt ex Property & RESI
Financials	29%	35%	29%
Industrials	71%	65%	71%

From Table 4.2.3.2 it is evident that the sector weightings are less extreme than was witnessed in the previous section (i.e. including Resources and Property shares from investable universe). However, a preference for Financials stocks is noticeable for the high volatility portfolio relative to the low volatility portfolio.

The next step that will be pursued is to run the back-test on a sector-neutral basis as this will eliminate any sector effects which may be inherent in the results presented thus far.

#### **4.2.4. Back-test results using Top 100 JSE shares with sector neutrality constraint**

In this section the back-test is run within sectors and then the low volatility and high volatility portfolios are constructed such that the sector weights (i.e. Resources, Financials, Industrials and Property) are the same as the ALSI 100 over time as shown below:

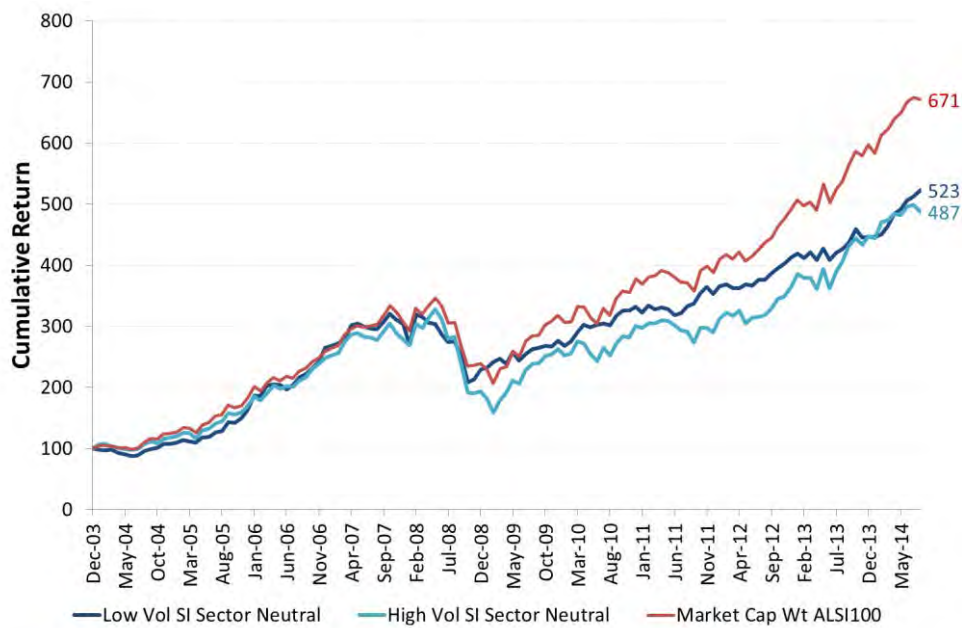
- At each quarter-end from December 2003 to August 2014 construct the low and high volatility portfolios within the Resources, Financials, Industrials and Listed Property JSE sectors.
- Assign the weights in the final low (high) volatility portfolio such that the sector weights of this portfolio are similar to those in the JSE ALSI100 at each quarter-end.

In essence this approach ensures that there are no sector biases within the portfolios and the observed out-of-period performance is as a result of the low or high beta stock selection within the sectors.

Figure 4.2.4.1 depicts the cumulative total returns of R100 invested in the low volatility, high volatility and market-cap weighted portfolios as at 31 December 2003 to 31 August 2014. On the figure the following abbreviations have been used:

- Low Vol SI Sector Neutral (Clarke *et al.* (2011) minimum variance portfolio constructed using JSE largest 100 shares with sector neutrality constraint)
- High Vol SI Sector Neutral (high volatility portfolio created using a derivation similar to Clarke *et al.* (2011) using JSE largest 100 shares with sector neutrality constraint)
- Market-cap Wt ALSI100 (market-cap weighted portfolio of the largest 100 JSE shares)

**Figure 4.2.4.1: Cumulative Returns using Top 100 shares with sector neutral constraint**



From Figure 4.2.4.1 both the low volatility and high volatility portfolios have underperformed the market-cap weighted portfolio. This can partially be explained by the fact that the imposition of sector constraints may distort the low volatility anomaly as was discussed in the previous section. More importantly, the low volatility portfolio has outperformed the high volatility portfolio (albeit with a small margin) out-of-period. In international literature the low volatility anomaly is described as the empirical finding that low volatility portfolios have been found to outperform high volatility portfolios at a lower risk, globally out-of-period. Thus the observed low volatility outperformance relative to the high volatility portfolio in this sector-neutral setting provides further evidence that the low volatility anomaly in the South African market cannot be attributed to merely a sector effect. As such it can be concluded that the low volatility anomaly is present in the South African market and is widespread within sectors, consistent with the findings of Baker *et al.* (2014) in the U.S. market.

In Table 4.2.4.1 below the statistical significance of this outperformance is tested using the market model regression as was defined in equation (9). The aim of this regression is to determine if the low volatility portfolio has a statistically significant positive alpha relative to the high volatility portfolio out-of-period in this sector-neutral setting.

**Table 4.2.4.1: ANOVA table obtained from Low – High Vol portfolio market model regression with sector neutrality constraint (December 2003 – August 2014)**

<i>Regression Statistics</i>	
Multiple R	58%
R Square	34%
Adjusted R Square	33%
Standard Error	3.23
Observations	128

ANOVA					
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	1	671.33	671.33	64.31	0%
Residual	126	1 315.40	10.44		
Total	127	1 986.74			

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
<b>Net Alpha (Low - High Vol)</b>	0.61	0.30	2.06	4%	0.03	1.19	0.03	1.19
<b>Net Beta (Low - High Vol)</b>	-0.43	0.05	-8.02	0%	-0.54	-0.33	-0.54	-0.33

The market model regression in Table 4.2.4.1 has explained 34% of the variation in the low volatility outperformance relative to the high volatility portfolio. While this R-squared is low, the statistically significant F-statistic with a p-value of 0% implies that the regression is statistically significant and can be relied upon. After including a sector neutrality constraint on the portfolios, the beta of the low volatility portfolio is statistically significantly (p-value of 0%) less than that of the high volatility portfolio by 0.43, out-of-period. The low volatility portfolio has a statistically significant (i.e. p-value of 4%) positive alpha of 0.61% relative to the high volatility portfolio out-of-period.

From the analysis in the above sections it can be concluded that the Property, FINDI vs. RESI sector effects have had a statistically significant effect on the low beta anomaly in the South African setting. However, when these sector effects were excluded from the portfolios (i.e. analysis excluding Property and RESI shares and the sector-neutral portfolios) the low volatility portfolio outperformance over the high volatility portfolio was found to have persisted and the low volatility portfolios were found to have had a statistically significant positive alpha relative to the high volatility portfolios out-of-period. In fact it can be concluded, consistent with Baker *et al.* (2014) and Asness, Frazzini and Pedersen (2014), that the low volatility effect (i.e. low volatility vs. high volatility portfolios) in the South African setting has been statistically significant at the stock selection level within sectors out-of-period. These results would suggest that the security market line in the South African market is flatter than is implied by the CAPM, consistent with Black (1972).

#### 4.2.5. Analysing the effect of the imposition of sector constraints on the low volatility anomaly in the South African market

In the previous section sector constraints were imposed on the portfolios to investigate if the low volatility anomaly has been merely as a result of a sector effect or if it has been widespread across the JSE sectors. In this section an in-depth analysis is performed on the portfolios before and after the imposition of sector constraints. This analysis will help determine the impact of the imposition of sector constraints on the low volatility vs. high volatility portfolio characteristics.

##### *Effect of sector constraints on portfolio composition*

To investigate the impact of the imposition of sector constraints on the portfolio compositions the active share as introduced by Petajisto (2013) is used; where active share is defined as follows:

$$Active\ Share = \frac{1}{2} \sum_{i=1}^n |w_{i,A} - w_{i,B}| \quad (14)$$

where  $n$  = total number of stocks in portfolio A and B

$w_{i,A}$  = weight of stock  $i$  in portfolio A

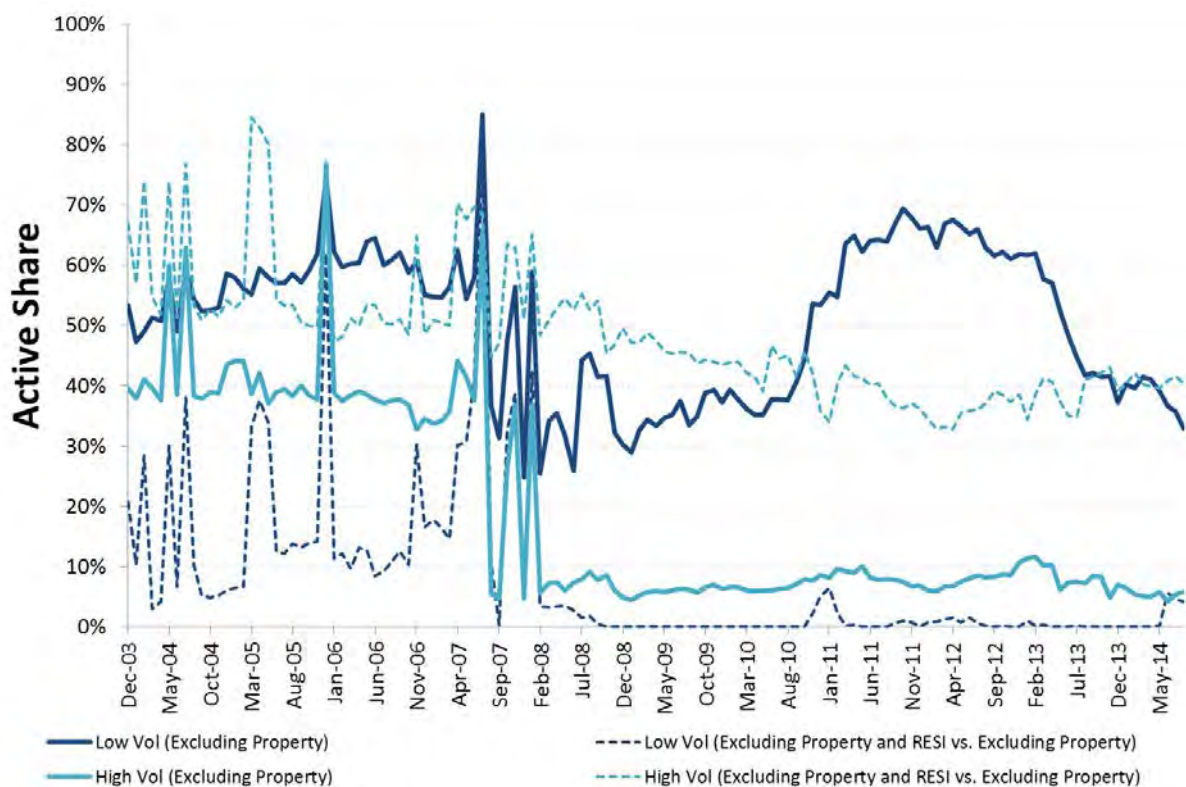
$w_{i,B}$  = weight of stock  $i$  in portfolio B

Essentially, the active share measures the absolute distance between two portfolios. In this setting the active share will be used to measure the distance between the sector-unconstrained portfolios vs. the portfolios excluding Property shares vs. the portfolios excluding Property and RESI shares. The aim is to understand the impact of imposing sector constraints on the composition of the low and high volatility portfolios. If the active share between the portfolios with and without sector constraints is found to be low, it would imply that the imposition of sector constraints has not had a material impact in altering the portfolio composition. As such the sector-constrained low and high volatility portfolios are still good approximations of the low and high volatility portfolios. Thus, the interpretation of the low volatility anomaly may still be relevant. However, if the active share resulting from the imposition of sector constraints is large; it would imply that the sector-constrained low and high volatility portfolios are very different to the sector-unconstrained low and high volatility portfolios. As such the interpretation of the low volatility and high volatility portfolio characteristics may not be an accurate reflection on the low volatility anomaly in that case.

Figure 4.2.5.1 below depicts the active share over time of the low and high volatility portfolios as follows:

- Solid **blue** and **green** lines: depict the active share of the low and high volatility portfolios after excluding Listed Property shares (i.e. distance between the low and high volatility portfolios before and after the Property constraint).
- Dotted **blue** and **green** lines – depict the additional active share of the low and high volatility portfolios after excluding Property and RESI shares (i.e. distance between the low and high volatility portfolios after the exclusion of Property and RESI shares vs. exclusion of Property shares only)

**Figure 4.2.5.1: Active Share of the low and high portfolios after the imposition of sector constraints**



From Figure 4.2.5.1 above it is evident that the exclusion of the Listed Property stocks has had a material impact on the composition of the low and high volatility portfolios. In particular, the imposition of this constraint (as depicted by the solid **blue line** in Figure 4.2.5.1) has resulted in an active share of at least 25%. This effectively implies that the exclusion of Property shares from the investable universe has resulted in at least a quarter of the stocks in the low volatility portfolio being substituted with stocks from a higher beta sector. In addition, the exclusion of the RESI shares from the investable universe also induces a further change in the low volatility portfolio composition (as depicted by the dotted **blue line** in Figure 4.2.5.1). This implies that the imposition of sector constraints has a material impact on the composition of the low volatility portfolio. As such the constraint on sector allocations may materially distort the interpretation of the low volatility anomaly in the South African market. This material imposition of sector constraints may explain the



observed underperformance of the low volatility portfolio relative to the market-cap weighted benchmark for the sector-neutral and Property & RESI sector-constrained portfolios.

#### *Effect of sector constraints on out-of-period portfolio return characteristics*

Blitz and van Vliet (2014) argue that low volatility stocks tend to outperform in sharply falling markets (e.g. 2008) and underperform in strongly rising markets (e.g. 2009). The outperformance from low volatility portfolios in falling markets is due to the fact these portfolios tend to fall to a lesser extent relative to high volatility portfolios in this market environment. Blitz and van Vliet (2014) show that from a global equity perspective; on average the low volatility portfolio outperformed the market-cap weighted benchmark in the case where the benchmark return was negative and in the case where the benchmark return was between 0% and 15%. On the other hand, when the 1 year benchmark return was greater than 15%; they showed that the low volatility portfolio underperformed the market-cap weighted benchmark.

Figure 4.2.5.2 depicts the average 1 year return of the low volatility, high volatility and market-cap weighted portfolios in the South African market during periods when the market-cap weighted benchmark delivered a 1 year return that is:

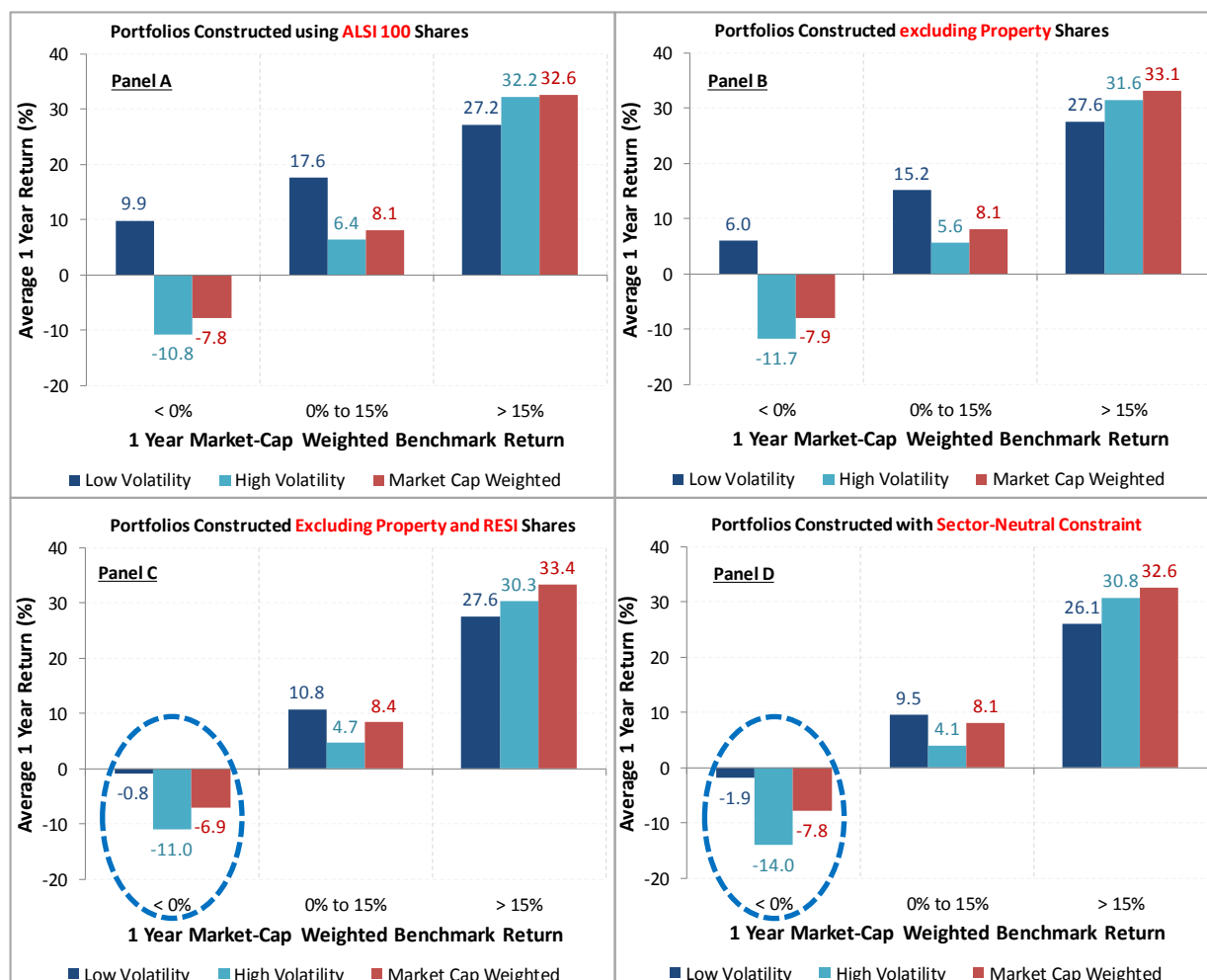
- Less than 0% (i.e. negative)
- Between 0% and 15%
- Greater than 15%

In Figure 4.2.5.2 the conditional 1 year returns have been partitioned into the following:

- i. **Panel A:** Portfolios constructed using ALSI100 universe
- ii. **Panel B:** Portfolios constructed using ALSI100 excluding Property shares
- iii. **Panel C:** Portfolios constructed using ALSI100 excluding Property and RESI shares
- iv. **Panel D:** Sector-neutral portfolios constructed using ALSI100 universe



**Figure 4.2.5.2: Average 1 Year Portfolio Returns in varying market environments (December 2003 – August 2014)**



From a South African perspective, Figure 4.2.5.2 above is consistent with the findings of Blitz and van Vliet (2014). On average the low volatility portfolios have outperformed the high volatility and market-cap weighted portfolios when the 1 year market return has been negative or between 0% and 15%. During periods when the market return was in excess of 15% the low volatility portfolios underperformed both the high volatility and market-cap weighted portfolios consistent with Blitz and van Vliet (2014). Figure 4.2.5.2 also highlights the effects of the imposition of sector constraints on the out-of-period portfolio characteristics as shown below:

- The exclusion of Property shares (Panel A vs. Panel B) has not had a material impact on the conditional returns of the low and high volatility portfolios relative to the market-cap weighted benchmark.
- The exclusion of Property and RESI shares (Panel C vs. Panel A & B) has had a material impact on the conditional returns of the low volatility portfolio. The imposition of this sector constraint has resulted in the performance being considerably worsened in negative markets (from +9.9% to -0.8%) while the performance of the high volatility and market-cap weighted portfolio has not been

materially affected in this market environment. This may explain the observed underperformance of the low volatility portfolio relative to the market-cap weighted portfolio when this sector constraint was imposed.

- c. Similarly, the imposition of the sector-neutrality constraint (Panel D vs. Panel A & B) has also had a material impact on the out-of-period conditional portfolio returns. Again, the performance of the low volatility portfolio is worsened considerably in negative markets (-1.9% vs. 9.9%) relative to the high volatility and market-cap weighted portfolios. This may explain the observed underperformance of the low volatility portfolio relative to the market-cap weighted portfolio in this sector-neutral environment.

Given that low volatility stocks tend to have smaller drawdowns than high volatility portfolios it can be expected that they recover more quickly from losses (see Blitz and van Vliet (2014) and Papathanakos and Musolf (2014)). The quicker recovery rate can be attributed to the asymmetry of the required return to break-even after experiencing a drawdown. This can be demonstrated using Siegel's paradox which was introduced in the foreign exchange market. In the low volatility vs. high volatility drawdown setting it would translate to the fact that the required positive return (to break-even) from a drawdown is higher than the negative return experienced in the drawdown. This is demonstrated in the example in Table 4.2.5.1 below:

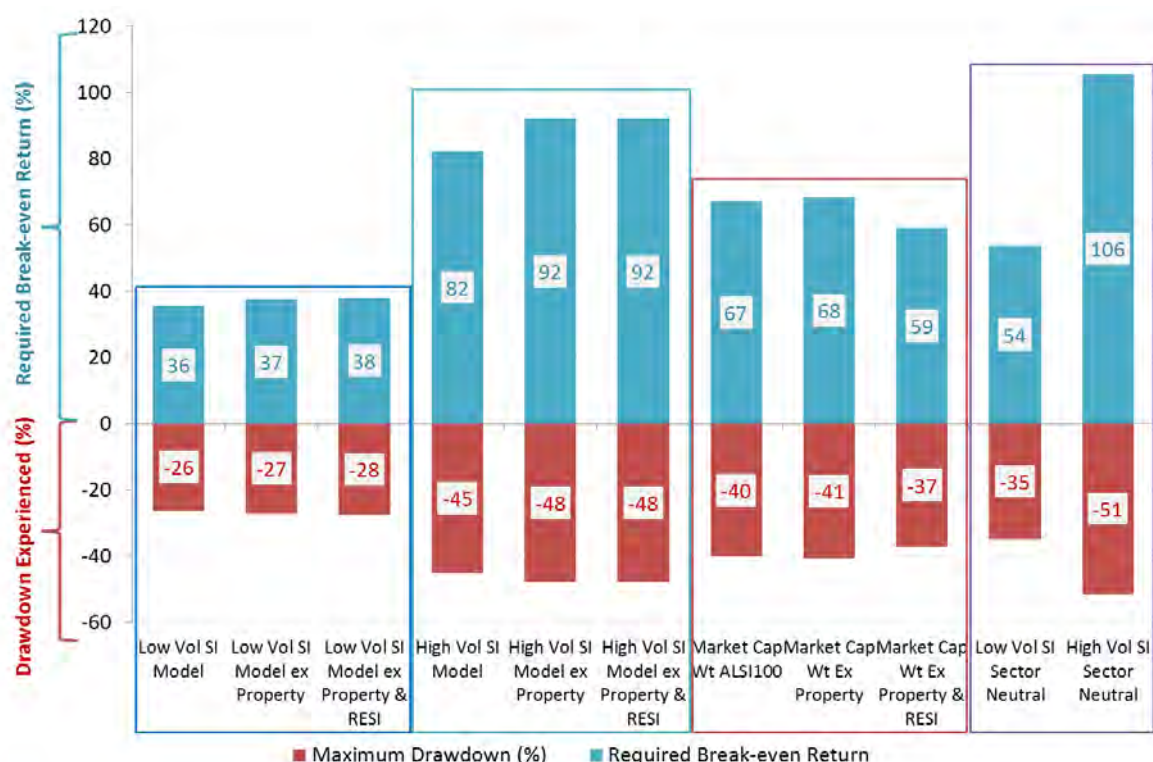
**Table 4.2.5.1: Drawdown vs. Required Return to break-even**

Drawdown Experienced vs. Required Return to Break-even									
Drawdown Experienced	-10%	-20%	-30%	-40%	-50%	-60%	-70%	-80%	-90%
Required Return to Break-even	11%	25%	43%	67%	100%	150%	233%	400%	900%

From Table 4.2.5.1 it is evident that for every level of drawdown experienced the required positive return to break-even is always greater than the drawdown experienced. For example if one experiences a drawdown of -50%; then one requires a positive return of 100% to break-even. Given that low volatility portfolios tend to experience lower drawdowns than high volatility portfolios (see Blitz and van Vliet (2014) and Papathanakos and Musolf (2014)), it would imply that the subsequent burden on low volatility portfolios to break-even is considerably smaller than that of the high volatility portfolios. As such, it would make sense that low volatility portfolios would recover more quickly from losses (to break-even) than high volatility portfolios.

Given their lower drawdowns (Figure 4.2.5.2), the low volatility portfolios would have a lower required return to break-even than the high volatility and market-cap weighted portfolios. Figure 4.2.5.3 below depicts the maximum drawdowns experienced by portfolios constructed in the South African setting and the required return to break-even after suffering the drawdown.

**Figure 4.2.5.3: Maximum Drawdown experienced vs. Required Break-even return (December 2003 – August 2014)**



It is evident from Figure 4.2.5.3 that the low volatility portfolios have had smaller maximum drawdowns than the high volatility and market-cap weighted portfolios in the South African market out-of-period. As a result these portfolios have required a considerably lower positive return to break-even than the high volatility and market-cap weighted portfolios. On the other hand the maximum drawdown experienced by the high volatility portfolios has been larger than that experienced by the market-cap weighted portfolios. As a result these portfolios have required a considerably larger return to break-even than both the low volatility and market-cap weighted portfolios. By imposing sector-neutrality the drawdown characteristics of the low volatility portfolio is worsened quite considerably as is evident in Figure 4.2.5.3 (last block on the right). As a result, the maximum drawdown of the sector-neutral low volatility portfolio is close to that of the market cap weighted portfolio (i.e. 35% vs. 40%). As such the required return to break-even for the sector-neutral low volatility portfolio is 54% which is materially higher than the other low volatility portfolios which ranged from 36% to 38%. This may explain why this portfolio underperformed the market-cap weighted portfolio.

Given the higher required return burden (to break-even) on the high volatility and market-cap weighted portfolios one would expect the low volatility portfolios to recover quicker. In Figure 4.2.5.4 below the maximum drawdown of the portfolios are depicted against the period it took to recover from the drawdown experienced. This will help establish if in fact

the smaller drawdowns experienced by low volatility portfolios have resulted in quicker recovery periods in the South African market.

**Figure 4.2.5.4: Maximum Drawdown vs. Period it took to Break-even (December 2003 – August 2014)**



From Figure 4.2.5.4 it is evident that the low volatility portfolios have recovered more quickly from the maximum drawdowns experienced than the high volatility and market-cap weighted portfolios in the South African market. This finding is consistent with international literature (see Blitz and van Vliet (2014) and Papathanakos and Musolf (2014)). Imposing sector-neutrality worsens the drawdown characteristic of the low volatility portfolio as it takes longer for this portfolio to recover from the maximum drawdown than the market-cap weighted portfolio and some high volatility portfolios. The above findings are consistent with international literature which argued that the low volatility effect can be explained by the fact that low volatility portfolios tend to have lower drawdowns than high volatility portfolios and recover from these more quickly.

Blitz and van Vliet (2014) showed that the compounding of returns over longer time horizons reduces this potential for underperformance in falling markets. In other words, if the investment period is lengthened then the probability of the low volatility portfolio underperforming in falling markets is materially reduced. Table 4.2.5.2 below depicts the probability of the low and high volatility portfolios underperforming the market-cap weighted portfolio over different investment horizons in the South African market.

**Table 4.2.5.2: Probability of underperformance during down markets (December 2003 – August 2014)**

Probability of Underperformance in Falling Markets	1 Month	3 Months	6 Months	12 Months	36 Months
Low Vol SI Model	21%	16%	13%	9%	3%
Low Vol SI Model ex Property	21%	17%	14%	9%	4%
Low Vol SI Model ex Property & RESI	26%	26%	27%	22%	18%
Sector Neutral Low Vol SI Model	33%	31%	33%	32%	28%
High Vol SI Model	47%	61%	65%	72%	84%
High Vol SI Model ex Property	58%	64%	68%	75%	87%
High Vol SI Model ex Property & RESI	62%	62%	65%	74%	86%
Sector Neutral High Vol SI	65%	76%	82%	90%	98%

While the low volatility portfolios have on average outperformed the high volatility portfolios in falling markets as can be seen in Table 4.2.5.2, there is a meaningful probability of the low volatility portfolio underperforming in falling markets. Importantly, this probability is reduced if the investment horizon is lengthened. On the other hand, lengthening the investment horizon increases the probability of the high volatility portfolios underperforming the market-cap weighted benchmarks in falling markets. Thus, lengthening the investment period allows for compounding to take effect and the risk characteristics of the low and high volatility portfolios become more pronounced. This is consistent with the findings of Baker *et al.* (2011) who argued that the characteristics of low volatility portfolios are more pronounced when looking at compound returns. From Table 4.2.5.2 it is also evident that imposing sector constraints on the portfolios materially worsens the low volatility portfolio performance in falling markets. For instance, imposing sector-neutrality increases the probability of underperformance in falling markets from 4% to 28% over 36 month periods. This material change in the out-of-period portfolio characteristics (after the imposition of sector constraints) may explain the underperformance of the low volatility portfolio relative to the market-cap weighted portfolio in the case where Property and RESI shares are excluded from the investable universe and the sector-neutral case.

From this section it can be concluded that low volatility portfolios do tend to outperform high volatility and market-cap portfolios in falling markets. The smaller losses experienced by the low volatility portfolios imply that the positive return required to break-even is considerably lower for low volatility portfolios; as such they recover more quickly from losses as has been evidenced. However, it is important to note the short-term risk of potential underperformance in falling markets as noted by Blitz and van Vliet (2014). The imposition of sector constraints exacerbates this risk as shown in Table 4.2.5.2. The risk of the low volatility portfolio underperforming in falling markets is reduced if the investment period is lengthened as compounding takes effect as shown by Blitz and van Vliet (2014).

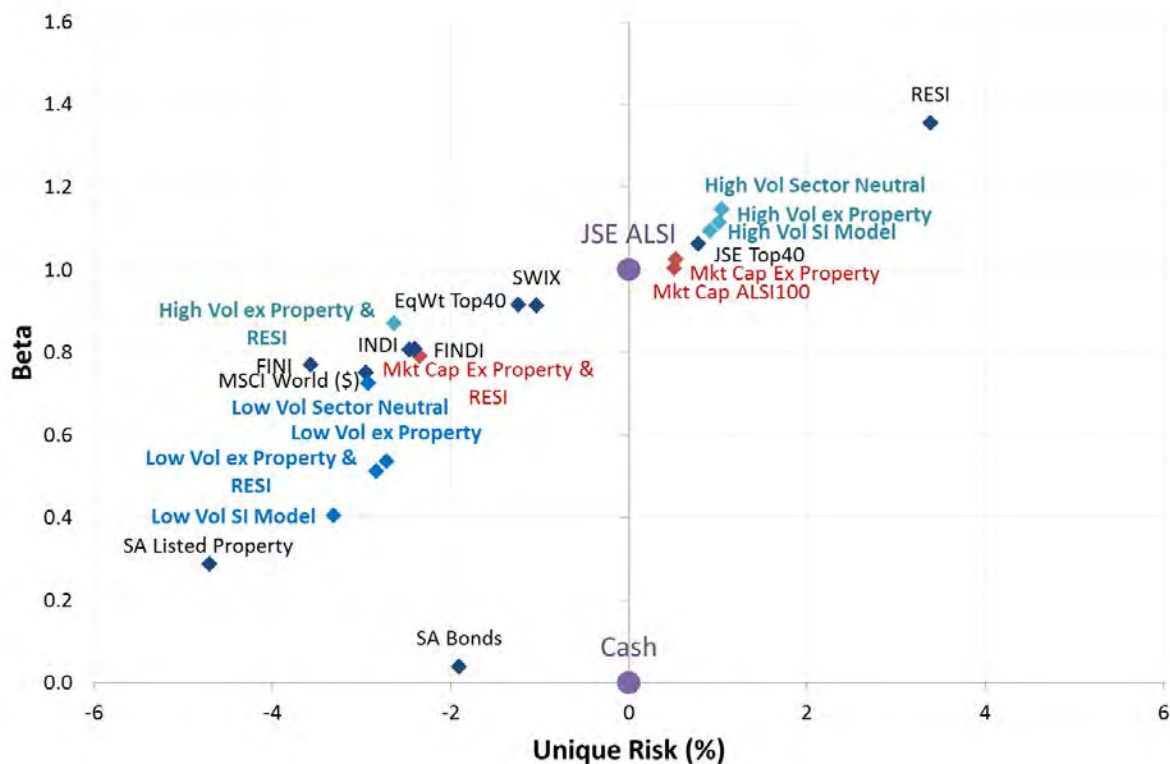
Thus far the impact of the imposition of sector constraints at the portfolio construction level has been analysed from a portfolio composition and drawdown perspective. In the ensuing

section the out-of-period risks of the portfolios (before and after the imposition of sector constraints) are analysed using the covariance bi-plot.

#### 4.2.6. Using the covariance bi-plot to analyse the out-of-period risk characteristics of the portfolios before and after the imposition of sector constraints

The covariance bi-plot as was introduced by Barr *et al.* (1990) will be used in this setting to assess the out-of-period risk characteristics of the low volatility vs. high volatility portfolios simultaneously (before and after the imposition of sector constraints).

**Figure 4.2.6.1: Covariance bi-plot of the low vs. high volatility portfolios (December 2003 – August 2014)**



From the covariance bi-plot in Figure 4.2.6.1:

- The low volatility portfolios have preserved their low volatility characteristics out-of-period; having lower beta and volatility than the high volatility portfolios.
- Before the RESI shares were excluded from the analysis the high volatility portfolios were positioned close to the RESI index, consistent with the overweight RESI position inherent in these portfolios.
- There is a low correlation between the low volatility portfolios and the high volatility portfolios before the exclusion of RESI shares from the analysis (i.e. the angle between the lines connecting Cash and these portfolios is close to 90 degrees implying very low correlation).

- After excluding RESI shares from the analysis there is a high correlation between the low and high volatility portfolios (i.e. the angle between the lines connecting Cash and these portfolios is close to 90 degrees implying very low correlation), indicating that the risk characteristics between these portfolios were no longer very distinct.
- By imposing sector neutrality on the low volatility portfolio, the beta of the low volatility portfolio increases from 0.4 up to 0.7. However, the sector neutral low volatility portfolio is very distinct from the sector neutral high volatility portfolio as is depicted by the positioning of these portfolios on the covariance bi-plot.
- The sector neutral high volatility portfolio is positioned very close to the other high volatility portfolios, indicating that adding sector neutrality as a constraint has not materially changed the risk characteristics of this portfolio.

All in all the exclusion of the Property and RESI shares from the investable universe and the imposition of the sector-neutrality constraint has resulted in materially different out-of-period risk characteristics for the low volatility vs. high volatility portfolios in the South African market. In addition, the active share showed that the imposition of these sector constraints resulted in low vs. high volatility portfolios that were materially different to the portfolios without sector constraints. Also, the imposition of sector constraints had a material impact on the out-of-period portfolio return characteristics. These material differences in the portfolio characteristics may explain the underperformance of the low volatility portfolio relative to the market-cap weighted portfolio after the imposition of the Property & RESI and sector-neutrality constraints on the portfolios. More importantly, the low volatility portfolio outperformed the high volatility portfolio before and after the imposition of sector constraints. From this it can be concluded that the low volatility anomaly is prevalent in the South African market and is widespread within sectors as opposed to it being merely a sector effect, consistent with Baker *et al.* (2014).



### ***4.3. Summary Findings on the Low Volatility Back-test in the South African market***

The Clarke *et al.* (2011) low volatility portfolio construction methodology was selected as the appropriate methodology for the purposes of this thesis. This choice was made as a result of the methodology's proximity to the CAPM and its improvements relative to the GMV portfolio. As such the back-test was run using this low volatility portfolio construction methodology.

The low volatility portfolio outperformed the market-cap weighted and high volatility portfolios in the South African market out-of-period, with a statistically significant (p-value 1%) out-of-period monthly alpha of 0.84%. Upon closer inspection the Listed Property and FINDI vs. RESI sector effects were detected as statistically significant at explaining the low volatility anomaly in the South African market. To investigate whether the low volatility anomaly is merely a result of these sector effects or if it is widespread across the JSE sectors, constraints were imposed on the sector composition within the low and high volatility portfolios.

The exclusion of both the Listed Property and RESI shares from the investable universe and the imposition of the sector-neutrality constraint resulted in the low volatility portfolio underperforming the market-cap weighted portfolio out-of-period. The imposition of these sector constraints was shown to have a material impact on the composition of the low and high volatility portfolios using the active share. In addition, these sector constraints were also shown to have materially changed the out-of-period risk and drawdown characteristics of the low and high volatility portfolios. This material distortion of the low volatility portfolio characteristics may explain the observed underperformance of this portfolio relative to the market-cap weighted portfolios.

More importantly, the low volatility portfolio outperformance relative to the high volatility portfolio was still prevalent after the imposition of sector constraints. Based on these findings it can be concluded that in the South African setting the Property and FINDI vs. RESI sector effects are significant factors in explaining the low volatility anomaly. However, it can also be concluded that the low volatility anomaly cannot be attributed to only a Listed Property or FINDI vs. RESI sector effects. This can be evidenced by the fact that the low volatility portfolios outperformed the high volatility portfolios with statistically significant positive out-of-period alphas after imposing the sector neutrality constraint and excluding both the Listed Property and RESI shares from the investable universe. Thus it is concluded that the low volatility effect is prevalent and statistically significant in the South African market within industries, consistent with the findings of Baker *et al.* (2014) and Asness *et al.* (2014) in the U.S. market.



## 5. Understanding the low volatility anomaly in the South African Equity market

From the back-test results in the previous section, low volatility portfolios have outperformed their high volatility counterparts, while preserving their low volatility characteristics out-of-period in the South African setting. From the statistical tests performed on these, the conclusion is that the outperformance cannot be attributed to only a sector effect. The sector-neutral low volatility portfolio constructed using the largest 100 JSE share universe still produced a positive monthly alpha of 0.61% over the high volatility portfolio with a p-value of 4% out-of-period. This is consistent with the findings of Baker *et al.* (2014) and Asness *et al.* (2014) in the U.S. market who found the low volatility effect to be more pronounced at the stock selection level within industries and countries than across industries or countries.

Yamada and Nagawatari (2010) argue that the price volatility of a stock should reflect the underlying expected earnings variability. As such the sector effect would be driven by the underlying sector expected earnings variability. This would imply that sectors with low or high variability in their expected earnings would, by construction, have overweight positions in the low or high volatility portfolios respectively. The imposition of sector constraints forces the low or high volatility portfolios to allocate to some sectors that they otherwise would not have allocated to. This in turn may result in some of the low or high volatility characteristics being lost because of the constraints. Thus, the analysis of the sector-neutral portfolios may not necessarily be a true test of the low volatility anomaly. On the other hand it was shown that the exclusion of Property stocks from the investment universe did not have a material impact on the out-of-period risk and return characteristics of the low and high volatility portfolios. It was concluded that the low and high volatility portfolios constructed with this constraint were still fairly good approximations of the low and high volatility portfolios with no sector constraints. Thus, the portfolios that will be used in the upcoming sections will be the ones where Listed Property stocks have been excluded from the investment universe.

The aim of this section is to try and explain the low volatility anomaly following international literature. A further aim is to determine if empirical evidence in the South African market supports the explanations given for the low volatility anomaly in international literature. The explanations for the low volatility anomaly that will be investigated in this thesis in the South African market are listed below:

1. Benchmarking as a limit to arbitrage (Baker *et al.* (2011))
2. Manager Compensation and Agency issues between investment managers and their clients (Baker and Haugen (2012))
3. Agency issues amongst investment professionals (Baker and Haugen (2012))
4. Analysts' Earnings Growth Forecast Bias (Hsu, Kudoh and Yamada (2013))

5. Investor overconfidence in growth forecasts for stocks with high earnings variability (Yamada and Nagawatari (2010), Hsu *et al.* (2013) and Dichev and Tang (2010))
6. Investor Preference for lotteries (Baker *et al.* (2011))

In this chapter the above-listed potential causes of the low volatility effect will be laid out and an attempt will be made to find evidence of them (if any) in the South African market.

### 5.1. Effect of Benchmarking as a limit to arbitrage

Baker, Bradley and Wurgler (2011) argue that benchmarking exacerbates the low volatility anomaly from a portfolio construction perspective. They argue that the reason institutional investors are not overweight low volatility stocks is a result of the benchmarking. Typically institutional managers are mandated to maximise the information ratio relative to a market-cap weighted benchmark, where the information ratio is defined as follows:

$$IR_p = \frac{R_p - R_b}{TE_{p,b}} \quad (15)$$

where  $IR_p$  = information ratio of *portfolio P*

$R_p$  = return of *portfolio P*

$R_b$  = return of *benchmark B*

$TE_{p,b}$  = tracking error of *portfolio P* relative to *benchmark B*

The investment manager is expected to maximise the information ratio through stock selection and without using leverage. Using information ratio is appealing because it makes it easy to assess the stock selection skill (i.e. numerator of equation (15)) of the investment manager relative to the relative risk taken to achieve the outperformance (denominator of equation (15)). However, an investment manager mandated to maximise the information ratio is less likely to exploit the low volatility anomaly all else equal as low volatility stocks will typically increase their tracking error to the market-cap weighted benchmark.

If there is extra demand for high volatility stocks, this should push up the price of higher risk stocks and thus decrease the subsequent returns and vice versa for low risk stocks. However, an institutional investor with a fixed benchmark is unlikely to exploit these mispricings. In fact, Baker *et al.* (2011) demonstrate that the manager is more likely to exacerbate the problem as shown in the example that follows.

The Security Characteristic Line (SCL) for security  $j$  ( $j=1, 2, \dots, N$ ) is of the form:

$$E(R_{j,t}) = R_{f,t} + \beta_j E(R_{mkt,t} - R_{f,t}) + \alpha_j \quad (16)$$

where  $E(R_{j,t})$  = expected return of stock  $j$  at time  $t$

$\alpha_j$  = alpha of stock  $j$  relative to the market index

$R_{f,t}$  = risk – free rate at time  $t$

$$\beta_j = \text{beta of stock } j \text{ to the market index}$$

$$R_{mkt,t} = \text{expected market return at time } t$$

From equation (16) it can then be shown that the expected outperformance for a stock  $j$  can be deduced as follows:

$$\begin{aligned} E(R_{j,t}) - E(R_{mkt,t}) &= R_{f,t} + \beta_j E(R_{mkt,t} - R_{f,t}) + \alpha_j - \{R_{f,t} + \beta_{mkt} E(R_{mkt,t} - R_{f,t}) + \alpha_{mkt}\} \\ &= \beta_j E(R_{mkt} - R_f) + \alpha_j - \{1 \times E(R_{mkt} - R_f) + 0\} \\ &= (\beta_j - 1)E(R_{mkt,t} - R_{f,t}) + \alpha_j \end{aligned} \quad (17)$$

From equation (17) it can then be shown that overweighting the stock by  $\pi_j$  will increase the expected active return (relative to the benchmark) of the portfolio by approximately:

$$\Delta E(R_p - R_{mkt}) = \pi_j \{(\beta_j - 1)E(R_{mkt} - R_f) + \alpha_j\} \quad (18)$$

Now suppose that:

- $E(R_{mkt} - R_f) = 10\%$
- beta of *Stock A* =  $\beta_A = 0.75$
- beta of *Stock B* =  $\beta_B = 1.25$
- Market Volatility =  $\sigma_{mkt} = 20\%$

From (18) it follows that overweighting the low beta **stock A** can be expected to increase the portfolio relative return by approximately:

$$\Delta E(R_p - R_{mkt}) = \pi_A \{(\beta_A - 1)E(R_{mkt} - R_f) + \alpha_A\} = \pi(-2.5\% + \alpha_A) \quad (19)$$

From equation (19) it follows that unless the expected alpha of stock A is at least 2.5% relative to the benchmark, overweighting this stock will reduce the overall portfolio relative return. For instance, even if stock A had a healthy expected alpha of 2% relative to the benchmark; overweighting this stock will decrease the expected portfolio excess return by a factor of 0.5% multiplied by the overweight position. Thus, this stock would only be a candidate for an overweight position only if its expected alpha is higher than 2.5%. As such a manager who is mandated to maximise information ratio would not include this stock in their portfolio unless its expected alpha was at least 2.5%. Thus, by construction lower beta stocks are more likely to be candidates for underweight positions rather than overweight positions.

On the other hand the following can be deduced for the high beta **stock B**:

$$\Delta E(R_p - R_{mkt}) = \pi_B \{(\beta_B - 1)(R_{mkt} - R_f) + \alpha_B\} = \pi_B(2.5\% + \alpha_B) \quad (20)$$

This derivation shows that stock B will always be a candidate for an overweight position unless its expected alpha fell below -2.5%. In other words, if stock B has an undesirable expected alpha of -2.0% it would still be a candidate for an overweight position in the portfolio simply because of its high alpha.

The above example also shows that even if stock A has the same expected alpha as stock B (say 2%), the manager is compelled to choose stock B from a portfolio construction perspective. This is consistent with the findings of Brennan (1993) and Brennan and Li (2008). This further suggests that benchmarking creates demand for the high volatility stocks and would make these stocks to be priced at a premium relative to low volatility stocks.

In the above section it has been shown, following Baker *et al.* (2011) that from a portfolio construction perspective a manager who aims to increase their ex-ante information ratio would demand a higher expected alpha from a low beta stock than a high beta stock. This finding by Baker *et al.* (2011) concluded that benchmarking exacerbates the low beta anomaly precisely because of the demonstration above.

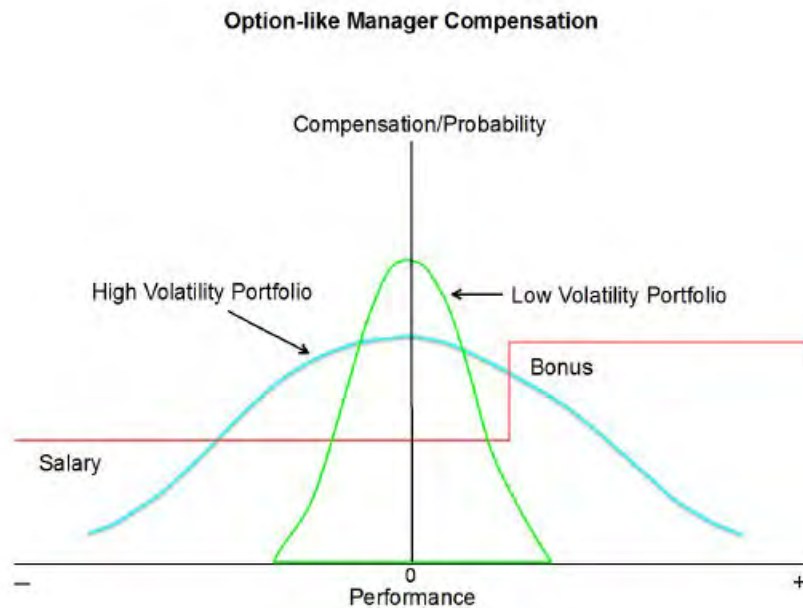
The following section examines the findings of Baker and Haugen (2012) in the South African market. They argued that manager compensation and agency issues between investment managers and their clients (including benchmarking) add to the low beta anomaly.

## **5.2. Effect of Manager Compensation & Agency issues between investment managers and their clients on the low volatility anomaly**

Baker and Haugen (2012) argued that manager compensation and agency issues between investment managers and their clients add to the low volatility anomaly. In particular they argued that the nature of manager compensation where an investment manager is paid a performance bonus if performance is above a given threshold benchmark exacerbates the low volatility anomaly. Baker and Haugen (2012) argued that an investment manager would increase their probability of achieving the performance threshold if they are invested in high volatility stocks. This argument is inter-linked with the argument of Baker *et al.* (2011) who argued that from a portfolio construction perspective investment managers would be inherently drawn to high volatility stocks (relative to low volatility stocks) if they are measured against a market benchmark. Together these arguments suggest that benchmarking creates excess demand for high volatility stocks which make them overpriced relative to low volatility stocks; which in turn would lead to lower subsequent returns for high volatility stocks relative to low volatility stocks.

Figure 5.2.1, sourced from the above-mentioned paper, is a depiction of how manager compensation can affect how an investment manager picks stocks depending on their compensation.

**Figure 5.2.1: Option-like Manager Compensation (Baker & Haugen (2012))**



The red line in Figure 5.2.1 depicts a hypothetical schedule of manager compensation where a manager is paid a base salary and then a bonus if performance is above a certain threshold. The green and the blue lines depict a hypothetical return distribution for a high and low volatility portfolio respectively. Comparing the return distributions of the low and high volatility portfolios it is evident that the low volatility portfolio has much less downside risk than the high volatility portfolio. However, the upside potential return of the low volatility portfolio is also much less than the high volatility portfolio.

From Figure 5.2.1 it is evident that an investment manager would maximise the probability of earning a bonus if they are invested in the high volatility portfolio rather than the low volatility portfolio. Blitz, Falkenstein and van Vliet (2014) argue that this incentive structure resembles a call option as the payoff for the investment manager can be depicted as:

$$MP_t = c + \max(R_{p,t} - X, 0) \quad (21)$$

where  $MP_t$  = manager payoff at time  $t$

$c$  = fixed base fee

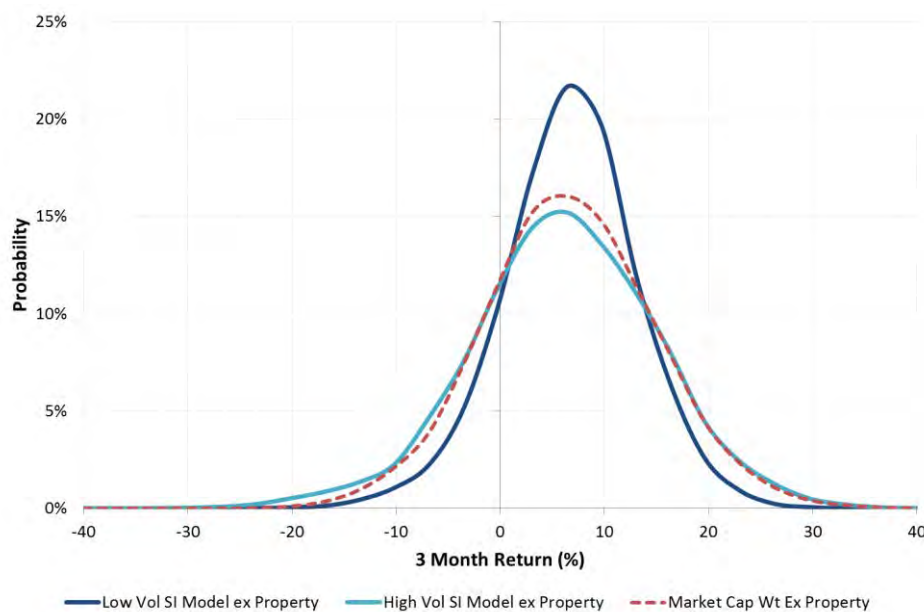
$R_{p,t}$  = portfolio return at time  $t$

$X$  = hurdle above – which manager receives performance bonus

Blitz *et al.* (2014) and Baker and Haugen (2012) argue that this agency issue between investment managers and their clients implies that the investment manager would have a preference for the high volatility portfolio as this would increase their probability of earning a performance bonus. This would imply more demand for high volatility stocks, implying that these would be priced at a premium relative to low volatility stocks.

Figure 5.2.2 below depicts the 3 month return distribution of the low volatility and high volatility portfolios in the South African market. Given that these are 3 month returns, they would only be an approximation of the long-term portfolio return distribution as they do not take into account the compounding effect.

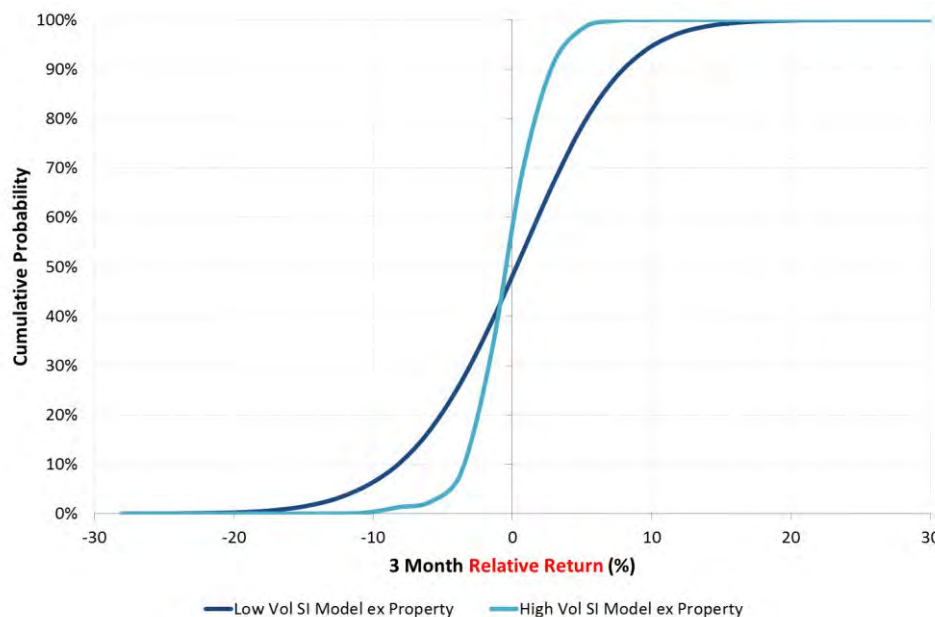
**Figure 5.2.2: 3 Month Absolute Return Distribution in the South African market (December 2003 – August 2014)**



The return distribution in Figure 5.2.2 of the low and high volatility portfolios is roughly consistent with that shown in Figure 5.2.1. In the South African setting, the high volatility portfolio has had significantly higher upside potential return than the low volatility portfolio. This portfolio has also shown slightly more upside potential than the market-cap weighted portfolio which would typically be the benchmark portfolio. On the other hand, the low volatility portfolio has shown very little upside return potential relative to both the market-cap weighted benchmark and the high volatility portfolio. On the downside; however, the low volatility portfolio has displayed materially better risk characteristics than both the market-cap weighted and the high volatility portfolio. However, an investment manager whose skill is measured on a relative basis would focus more on the relative performance (i.e. relative to the mandated market-cap weighted benchmark) rather than the absolute return distribution.

In general a fund manager is mandated to outperform a market benchmark as was shown in the previous section, consistent with Baker *et al.* (2011). Figure 5.2.3 below depicts the cumulative probability distribution of the 3 month relative outperformance of the portfolios relative to the market-cap weighted benchmark in the South African market.

**Figure 5.2.3: 3 Month Relative Return Cumulative Probability Distribution (December 2003 – August 2014)**

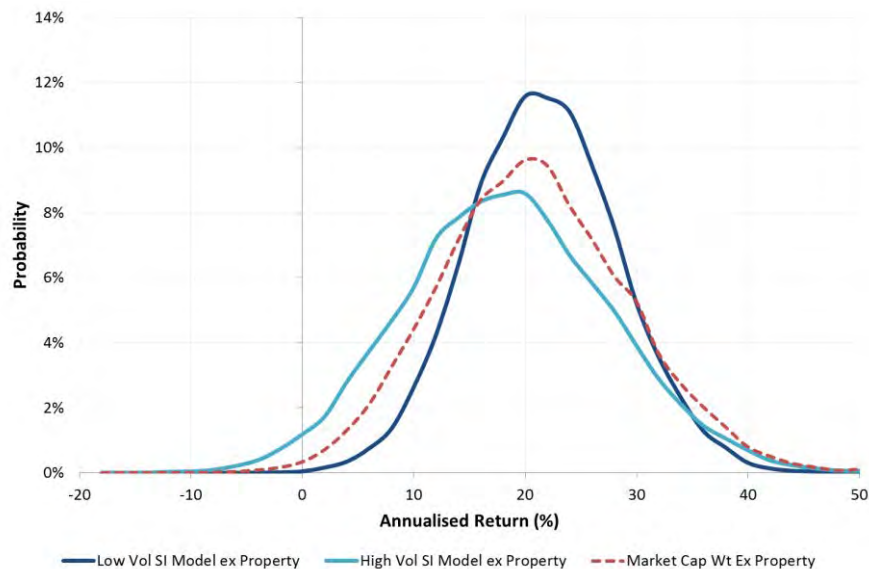


From Figure 5.2.3 it is evident that the low volatility portfolio has better upside relative return potential than the high volatility portfolio. However, the downside relative risk of this portfolio is significantly higher than the high volatility portfolio. For instance, there is a 10% probability of this portfolio underperforming the market-cap weighted benchmark by  $\pm 10\%$  on a 3 month basis. These downside relative risk characteristics of the low volatility portfolio may be undesirable for an investment manager whose compensation is dependent on their performance relative to the market-cap weighted benchmark.

By construction, an investment manager who is mandated to outperform or maximise the information ratio relative to the market-cap weighted benchmark would prefer the high volatility portfolio over the low volatility portfolio. While this portfolio has a higher probability of underperforming the market-cap weighted portfolio than the low volatility portfolio (i.e. 60% vs. 50%), the magnitude of underperformance is significantly lower. Secondly, the return distribution of this portfolio is much closer to that of the market-cap weighted benchmark than the low volatility portfolio. In other words, an investment manager mandated to outperform relative to a market-cap weighted benchmark would (by default) forgo the appealing absolute risk-return characteristics of the low volatility portfolio in favour of the relative risk-return characteristics of the high volatility portfolio. This would support the view of an agency problem existing between the investment managers and their clients as shown by Baker and Haugen (2012). In addition, this would also support the view of Baker *et al.* (2011) that benchmark constraints and arbitrage limits also contribute to exacerbate the low volatility anomaly. Given that Figure 5.2.2 and 4.2.3 show short term return distributions (i.e. 3 months) they fail to take into consideration the compounding effects. Baker *et al.* (2011) note that the advantage of low risk portfolios (relative to high

risk portfolios) is more pronounced when displayed in compound returns rather than average returns. To demonstrate this Figure 5.2.4 depicts the 60 month return distribution of these portfolios.

**Figure 5.2.4: 5 Year Return Distribution (December 2003 – August 2014)**

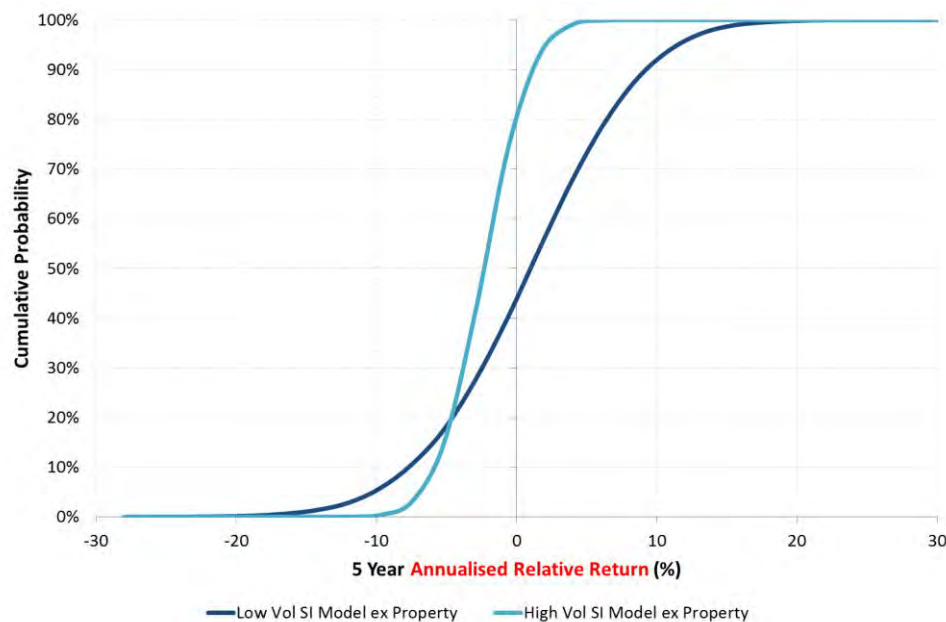


Extending the period to 5 years (as shown in Figure 5.2.4) allows for compounding to take effect. As such it can be seen that the low volatility portfolio is still very unlikely to yield extremely high returns. However, the likelihood of the high volatility and market-cap weighted portfolios achieving these returns is also reduced significantly but is still higher than the low volatility portfolio, albeit marginally. On the upside, the high volatility portfolio is more likely to earn an investment manager a performance bonus above a certain threshold than the low volatility portfolio.

Figure 5.2.5 shows the cumulative probability over the 5 year relative returns (relative to the market-cap weighted benchmark) of the low and high volatility portfolios. The appealing feature of this chart is that, unlike Figure 5.2.3 (i.e. 3 month chart), the longer investment horizon encompasses compounding.



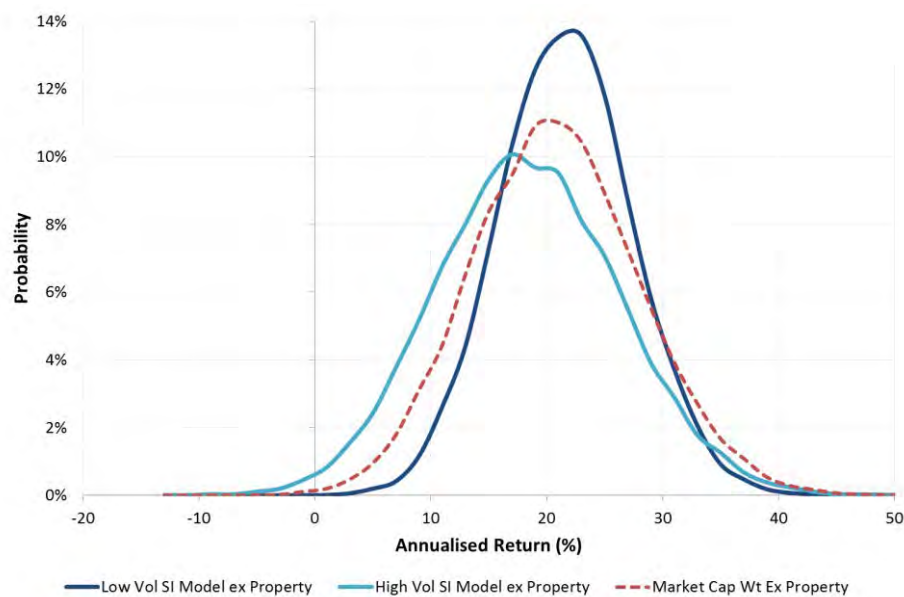
**Figure 5.2.5: 5 Year Relative Return Cumulative Probability Distribution (December 2003 – August 2014)**



As a result of compounding, the probability of underperformance is considerably reduced for the low volatility portfolio and magnified for the high volatility portfolio. On a 5 year basis (Figure 5.2.5) the low volatility portfolio has a 40% probability of underperformance while the high volatility portfolio has a probability of 80%. However, the magnitude of the underperformance is significantly lower for the high volatility portfolio. For instance, there is a 5% probability of the low volatility portfolio underperforming the market-cap weighted benchmark by 10% p.a. over 5 years. On the other hand the probability of the high volatility portfolio underperforming by 10% p.a. over a 5 year period has been 0%. Clearly, an investment manager who is measured against the market-cap weighted benchmark would be taking on materially higher downside relative risk if they were invested in the low volatility portfolio rather than the high volatility portfolio. This further demonstrates that, by construction, benchmarking would induce a demand for high volatility stocks than low volatility stocks (as argued by Baker *et al.* (2011)).

Extending the investment horizon to 7 years allows for the compounding effect to be more pronounced for the low volatility portfolio, in support of Baker *et al.* (2011) who argued that the low volatility effect is more pronounced when one looks at compound returns.

**Figure 5.2.6: 7 Year Return Distribution (December 2003 – August 2014)**



From Figure 5.2.6 one could argue that the low volatility portfolio return distribution is significantly better than that of the high volatility portfolio. This further supports the assertion by Baker *et al.* (2011) that the advantage of low volatility portfolios relative to the high volatility portfolio is greater when displayed in compound returns rather than average returns. The assertion that: “low volatility portfolios have lower drawdowns than high volatility portfolios and can thus recover more quickly from these than high volatility portfolios” is consistent with this finding.

Figure 5.2.7 below depicts the cumulative probability of outperformance over a 7 year investment period of the low and high volatility portfolios.

**Figure 5.2.7: 7 Year Relative Return Cumulative Distribution (December 2003 – August 2014)**

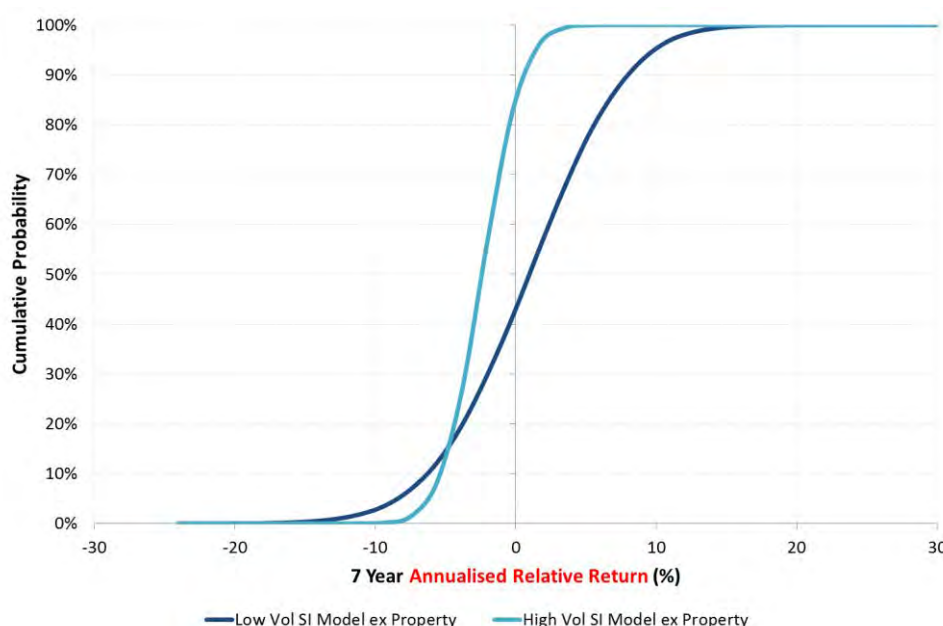


Figure 5.2.7 is consistent with Figure 5.2.5 (i.e. 5 year relative return distribution). While the relative return distribution of the low volatility portfolio may be superior to that of the high volatility portfolio, the potential of material underperformance (relative to the market-cap weighted benchmark) inherent in this portfolio may be unattractive for an investment manager mandated to outperform a market-cap weighted benchmark. Again, this portfolio has underperformed the market-cap weighted benchmark with a 40% probability while the high volatility portfolio has underperformed with an 85% probability over a 7 year period.

The above charts demonstrate why an investment manager, who is mandated to outperform a market-cap weighted benchmark, may be forced into the underperforming high volatility portfolio. Baker and Haugen (2012) argue that this would lead to higher demand for high volatility stocks than low volatility stocks. They then argue that this would imply that high volatility stocks are priced at a premium relative to low volatility stocks.

**Table 5.2.1: Skewness of outperformance (December 2003 – August 2014)**

Period	Low Vol SI Model ex Property	High Vol SI Model ex Property
3 Months	-0.18	-0.34
6 Months	-0.21	-0.16
12 Months	-0.24	0.04
36 Months	-0.17	-0.04
60 Months	-0.12	-0.03
84 Months	-0.11	-0.02

From Table 5.2.1 it is evident that the outperformance (relative to the market-cap weighted benchmark) of low volatility portfolio is more negatively skewed than the high volatility portfolio. This implies that the low volatility portfolio has a high probability of outperforming the market-cap weighted benchmark; however, there is a small probability of this portfolio yielding extreme underperformance relative to the market-cap weighted benchmark. An investment manager who is mandated relative to a market-cap weighted benchmark may find this feature of low volatility portfolios unappealing. On the other hand the outperformance of the high volatility portfolio, especially over longer-periods (i.e. 12 – 84 months), is not materially negatively skewed relative to the market-cap weighted benchmark. This would imply that this portfolio is less likely to yield extreme underperformance (relative to the market-cap weighted benchmark) than the low volatility portfolio. Thus, a manager would minimise the probability of extreme underperformance if they were invested in the high volatility portfolio relative to the low volatility portfolio.

In the above section the findings in the South African market have been similar to those of Baker and Haugen (2012), Baker *et al.* (2011) and Blitz *et al.* (2014). They found that investment managers who are compensated with a performance fee would maximise the probability of achieving the performance fee if they were invested in high volatility stocks rather than low volatility stocks. The findings in the above section also showed that from an absolute return basis the return characteristics of the low volatility portfolio are appealing relative to the high volatility portfolio. However, the relative performance of this portfolio (relative to the market-cap weighted benchmark) was found to be more risky than the high volatility portfolio. The relative returns of this portfolio (relative to the high volatility portfolio) were found to possess significantly more negative skewness. A manager who is mandated relative to the market-cap weighted benchmark would be taking on unwanted relative risk by investing in the low beta stocks, decreasing their probability of earning a performance fee. As such, an active manager would be incentivised to avoid low beta stocks and rather invest in high beta stocks to minimise the chances of extreme underperformance on their part. This would induce excess demand for high beta stocks leading them to be overpriced (relative to low beta stocks), implying lower subsequent returns for these stocks.

Baker and Haugen (2012) further argue that agency issues amongst investment professionals also add to the anomaly. In the following section this argument is tested in the South African setting.

### 5.3. Effect of Agency issues amongst investment professionals on the anomaly

Baker and Haugen (2012) further argue that a second agency problem exists amongst investment professionals within an organization. Their argument is that within an organization periodic investment committee meetings are central to the process of building a model portfolio which will serve as a guide for the construction of individual client portfolios. During these meetings the analysts, specialising in particular sectors, make a case for stocks they believe should be included in the model portfolio. Failing to make their case continually could result in stagnation or termination as opposed to career advancement. As a consequence, these analysts could be more attracted to stocks for which they can confidently make a compelling case. These stocks tend to be noteworthy and receive more media coverage; however, they also tend to exhibit higher than average volatility. This then implies that higher volatility stocks would be more likely to be included in the model portfolio than low volatility stocks. This agency issue would also further imply that high volatility stocks are more likely to be priced at a premium relative to low volatility stocks.

This argument by Baker and Haugen (2012) methodology is tested in the South African context following the methodology outlined below.

#### **Analyst Coverage Methodology:**

The aim in this section is to establish if high volatility stocks receive more analyst coverage than low volatility stocks in the South African market. If this is found to be the case; it would support the argument of Baker and Haugen (2012) that these stocks are more likely to be included in the model portfolio than low volatility stocks and help in explaining the low volatility anomaly. To test if this is the case; the back-test was conducted in the South African market as shown below.

Over the period 31 December 2003 to August 2014, at each month-end:

- I. Find the largest 100 JSE listed shares using the All Share weights from the BNP Paribas Cadiz database.
- II. Using Bloomberg find the total number of sell-side analysts with “BUY”, “SELL” and “HOLD” recommendations on each of these stocks.
  - The total number of “BUY”, “SELL” and “HOLD” recommendations will be added up and assumed to be the total sell-side analyst coverage for each stock as of that particular month-end.
- III. Calculate the percentage of analysts issuing a “BUY”, “SELL” or “HOLD” recommendation on each stock and this will be used as the percentage of “BUY”, “SELL” and “HOLD” recommendations out of the total coverage.

The average coverage per stock in a portfolio is calculated as follows at each month-end:

$$Avg_{cov_{p,t}} = \frac{\sum_{i=1}^n A_{c_{i,t}}}{n} \quad (22)$$

where  $Avg_{cov_{p,t}}$  = average analyst coverage per stock for portfolio  $P$  at time  $t$

$n$  = total number of stocks in portfolio  $P$  at time  $t$

$A_{c_{i,t}}$  = total number of Buy, Hold and Sell recommendations for stock  $i$  at time  $t$

Figure 5.3.1 depicts the average number of sell-side analysts covering a stock in the high and low volatility portfolios as well as the market-cap weighted portfolio over the period December 2003 to August 2014.

**Figure 5.3.1: Average Analyst Coverage per Stock (December 2003 – August 2014)**



The stocks in the low volatility portfolio have consistently received less analyst coverage than those in the high volatility portfolio. This finding in the South African market is consistent with that of Baker and Haugen (2012) who argued that high volatility stocks receive more analyst coverage than low volatility stocks. They argue that by virtue of their higher analyst coverage, high volatility stocks are more likely to be included in the model portfolio than low volatility stocks. They argue that this goes a long way in explaining why high volatility stocks could be priced at a premium relative to low volatility stocks. However, this is only one side of the equation as it only shows the total coverage and not the analyst views (i.e. buy vs. sell vs. hold recommendations). If the higher analyst coverage can be found to be accompanied by more optimism for high volatility stocks than low volatility stocks; this would support the above argument of Baker and Haugen (2012) from the South African perspective.

Figure 5.3.2 shows the percentage of “Buy” (out of the total number of “Buy”, “Hold” and “Sell”) recommendations in the high and low volatility portfolios over the period December 2003 to August 2014 in the South African setting.

**Figure 5.3.2: Percentage of BUY Recommendations (December 2003 – August 2014)**



Evidently, analysts in the South African market have issued more “Buy” recommendations for the high volatility portfolio than the low volatility portfolio almost consistently over time. Combining Figure 5.3.1 and Figure 5.3.2 shows that there has been more analyst coverage per stock for the high volatility portfolio than the low volatility portfolio. Secondly, the higher coverage has also been accompanied by a higher percentage of “Buy” recommendations. These findings in the South African market strongly support the argument put forth by Baker and Haugen (2012) that high volatility stocks are more likely to be included in the model portfolio than low volatility stocks. This would imply excess demand for high volatility stocks, making them to be priced at a premium relative to low volatility stocks. This in turn would lead to lower subsequent returns for high volatility stocks, partially explaining the low volatility anomaly.

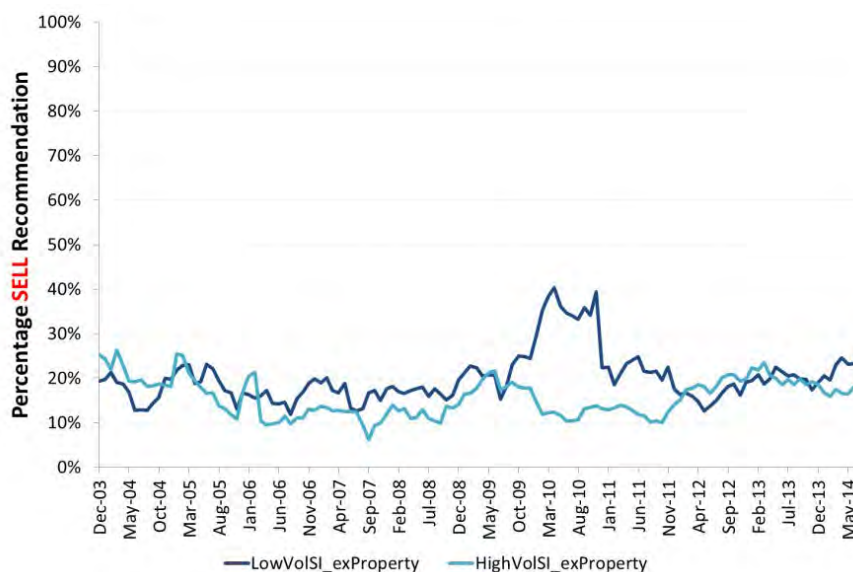
Figure 5.3.3 below depicts the percentage of Hold recommendations within the low and high volatility portfolios.

**Figure 5.3.3: Percentage of HOLD Recommendations (December 2003 – August 2014)**



In the South African market analysts have generally issued more “Hold” recommendations for the low volatility portfolio than the high volatility portfolio.

**Figure 5.3.4: Percentage of SELL Recommendations (December 2003 – August 2014)**



From Figure 5.3.4 analysts in the South African market have issued more “Sell” recommendations (fairly consistently over time) for the low volatility portfolio than the high volatility portfolio.

The above charts suggest that analysts have preferred high volatility stocks instead of low volatility stocks in the South African market. In addition, they have held more negative views on low volatility stocks than high volatility stocks. Baker *et al.* (2011) argue that stocks with more coverage (i.e. analyst, media etc.) will have more optimists among their shareholders. Combining these results with Miller (1977) that prices are generally set by



optimists it would imply that the high volatility stocks are generally priced at a premium relative to low volatility stocks, leading to lower future returns. This is consistent with the assertion of Baker and Haugen (2012) that this agency mispricing would mean that high volatility stocks are priced at a premium relative to low volatility stocks.

Thus far it has been shown that there has been more analyst coverage for larger and higher beta stocks than for low volatility stocks in the South African market. Baker and Haugen (2012) found a strong positive linear relationship between a stock's analyst coverage and its market capitalisation and its volatility. To test this relationship in the South African market the following cross-sectional regression analysis is performed over time following Baker and Haugen (2012):

$$\text{Stock Analyst Coverage} = \gamma * \text{Market Beta} + \tau * \text{market} - \text{cap weight} + \text{Constant} \\ A_{C_{i,t}} = \gamma\beta_{i,t} + \tau w_{i,t} + \varphi \quad (23)$$

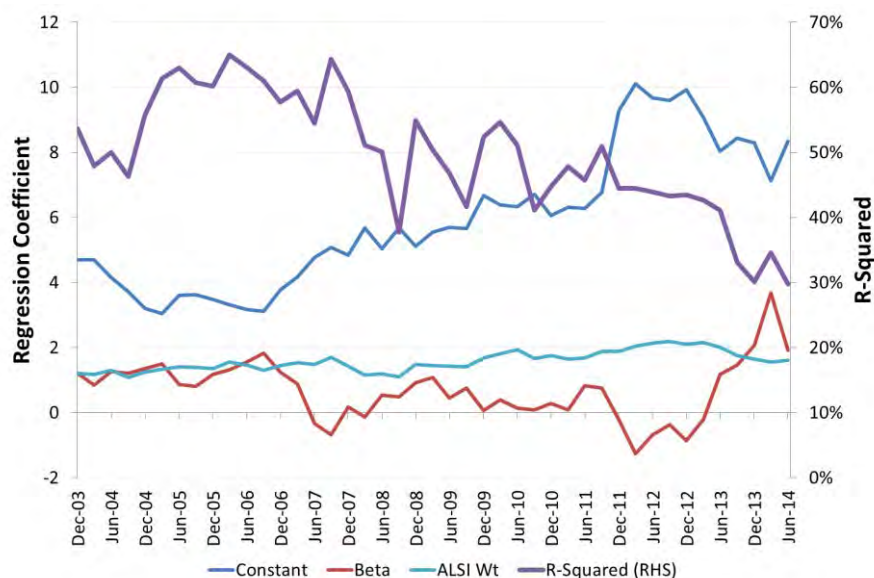
$A_{C_{i,t}}$  = total number of *Buy, Sell and Hold* recommendations for stock  $i$  at time  $t$

$\beta_{i,t}$  = beta of stock  $i$  at time  $t$  to the market cap weighted index

$w_{i,t}$  = market cap weight of stock  $i$  at time  $t$

The aim of this regression analysis is to help determine if a stock's analyst coverage has a significant relationship with its beta and market-cap weight in the South African setting.

**Figure 5.3.5: Regression coefficients for the Stock Beta and ALSI Weight Variables**

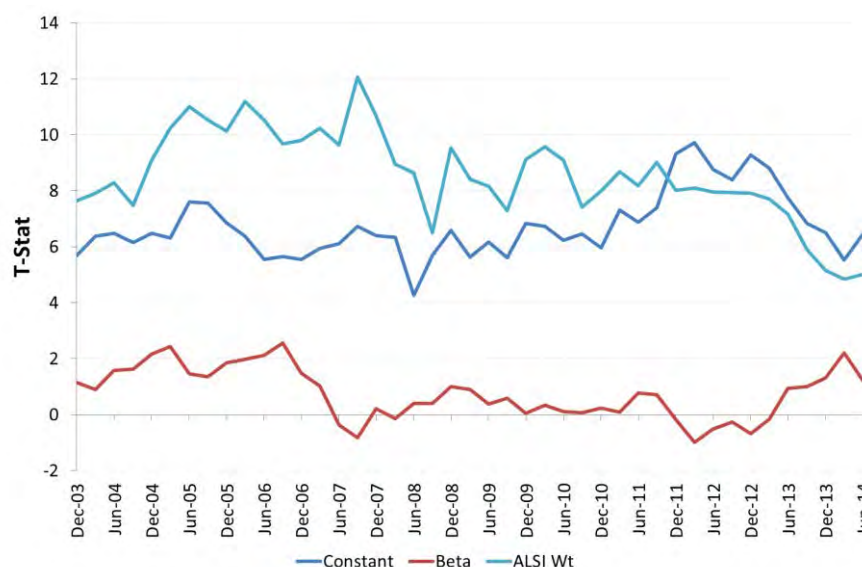


From Figure 5.3.5 it is evident that the R-squared from the regression analysis has been on a decline over time. Historically, the stock's ALSI weight and its beta have explained approximately 60% of the variation in analyst stock coverage; however, this has been on a decline and the R-squared was only 30% as of June 2014. All else equal, the average analyst coverage per stock has increased over time. As of June 2014 the average analyst coverage per stock was 8 analysts, ceteris Paribus. On average the analyst coverage per stock has

increased by 2 analysts for every 1% increase in a stock's weight in the ALSI while the analyst coverage per stock has been generally independent of the stock's beta. Thus, in the South African market the stock coverage (by sell-side analysts) has had a positive relationship with its weight in the ALSI (i.e. as a stock's weight in the ALSI increases its analyst coverage has also increased); consistent with Baker and Haugen (2012).

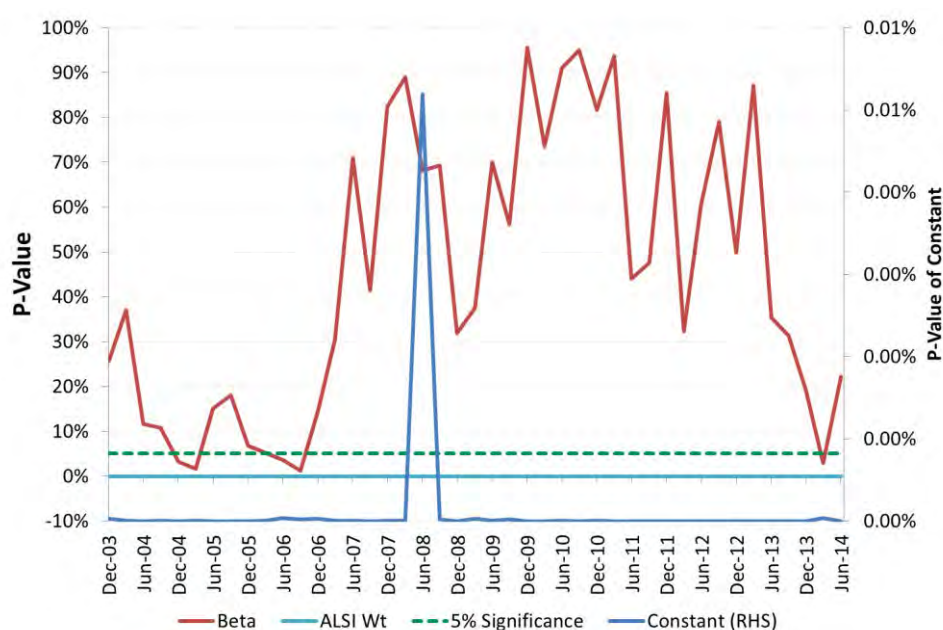
In Figure 5.3.6 below the t-statistics of the above regression coefficients are depicted.

**Figure 5.3.6: Analyst Coverage regression T-statistics (December 2003 – August 2014)**



From Figure 5.3.6 the weight of a stock in the market-cap weighted index has been a significant variable at explaining the analyst coverage. Holding all else constant, stocks with a higher weight in the market-cap weighted index have experienced significantly more analyst coverage over time. On the other hand the t-statistic for the beta was significant (around 2) over the period December 2003 to November 2006 and more recently between December 2013 and June 2014. Over the period December 2006 to November 2013 we cannot conclude that the relationship between analyst coverage per stock and stock beta was different from zero.

**Figure 5.3.7: Analyst Coverage regression P-values (December 2003 – August 2014)**



Evidently (Figure 5.3.7) the ALSI weight is significant at the 5% level as shown above. Thus, the stock weight in the market-cap weighted benchmark has a significant positive relationship to the analyst coverage. On the other hand, the stock beta has not had a significant p-value over this period. As such we cannot conclude that there is a significant relationship between a stock's beta and the number of analysts covering it.

Before concluding that the above holds, it is important to check if any of the multivariate linear regression assumptions are violated. If there is a significant correlation between the independent variables it could mean that a multi-collinearity problem exists in the regression analysis which could distort the results. This problem could result in the standard errors being higher than they should be and thus making the t-statistics too small. As a result it would mean one is more likely to disregard a relationship that truly exists as not being significant. Figure 5.3.8 below depicts the correlation between the two independent variables, namely stock beta and market-cap weight.

**Figure 5.3.8: Correlation between Stock Beta and ALSI Weight (December 2003 – August 2014)**

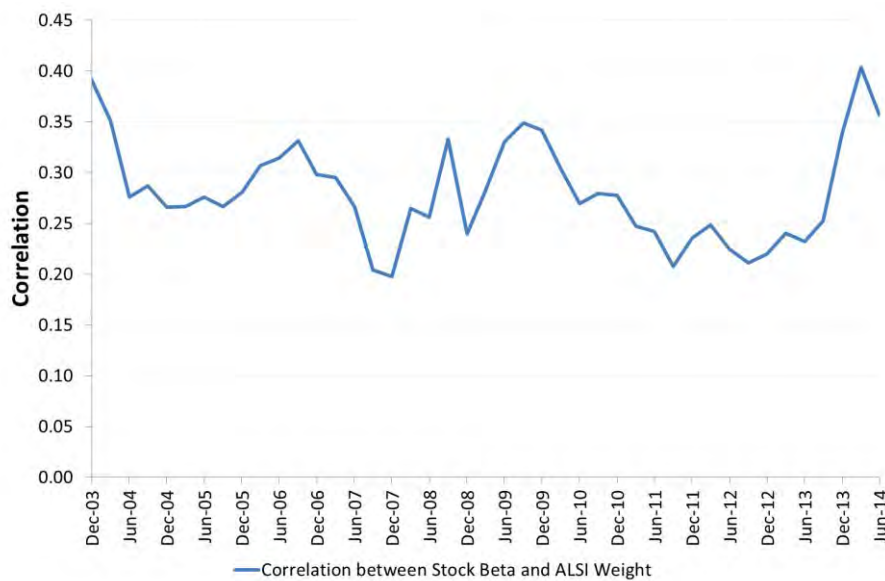


Figure 5.3.8 shows a consistent positive correlation between a stock's beta and its weight in the market-cap weighted benchmark. The correlation between these two variables has averaged 0.28; however, more recently this correlation increased to 0.35 as of June 2014. As such, this increase in correlation between the independent variables could potentially distort the regression results.

Given the multi-collinearity potentially inherent in the previous regression analysis, the Xiong *et al.* (2010) methodology may be a better model of identifying if there is a relationship between a stock's analyst coverage and its ALSI weight and beta. Following this methodology the analyst coverage for a stock can be decomposed into the following components:

$$A_{C_{i,t}} = w_{i,t} + (A_{C_{i,t}} - \beta_{i,t}) + (\beta_{i,t} - w_{i,t}) \quad (24)$$

where  $A_{C_{i,t}}$

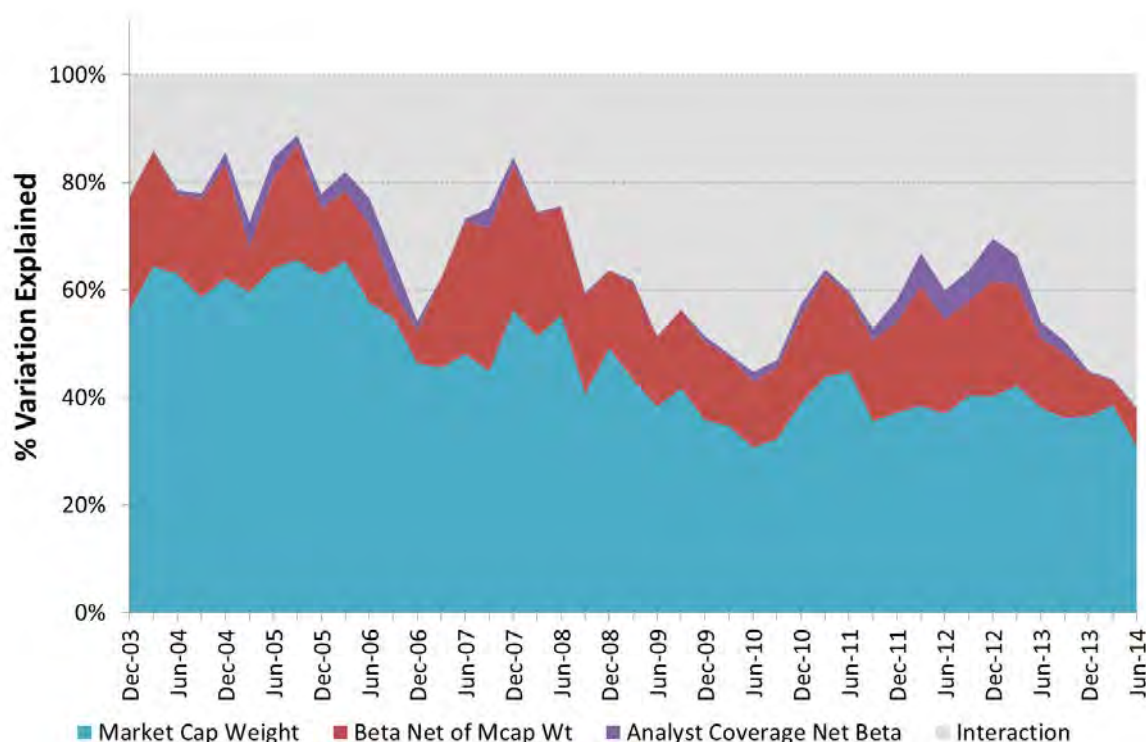
= total number of *Buy, Sell and Hold* recommendations for *stock i* at time *t*

$\beta_{i,t}$  = beta of *stock i* at time *t* to the market – cap weighted index

$w_{i,t}$  = market – cap weight of *stock i* at time *t* in the market  
– cap weighted index

Figure 5.3.9 depicts the percentage variation in analyst coverage per stock explained by the stock's beta and market-cap weight over time in the South African market.

**Figure 5.3.9: Variation in Stock Coverage Explained by Market-cap Weight and Stock Beta**



From Figure 5.3.9 above it can be concluded that:

- The market-cap weight has explained at least 30% of the variation in analyst coverage per stock over the period December 2003 to August 2014.
- However, the explanatory power of this variable has been declining over time. This could also be as a result of the introduction of the FTSE/ JSE Shareholder Weighted index (SWIX) as a benchmark.
- The beta (net of the market-cap weight) has explained between 4% and 27% of the variation in analyst coverage per stock.
- Together these variables (i.e. stock market-cap weight and beta) have explained between 38% and 88% of the variation in analyst coverage per stock over time.
- However, the explanatory power of these variables has been declining over time. As of June 2014 these two variables explained 38% of the total variation in analyst coverage per stock in the JSE.

From the above analysis it can be concluded that stocks with a higher weight in the market-cap weighted index and higher beta have generally received more analyst coverage in the South African market. Baker *et al.* (2011) argue that stocks with more coverage (i.e. analyst, media etc.) will have more optimists among their shareholders. Combining these results with Miller (1977) that prices are generally set by optimists it would imply that the high volatility stocks are generally priced at a premium relative to low volatility stocks, leading to lower future returns.

#### 5.4. Equity Analysts' Earnings Growth Forecast Effect on the anomaly

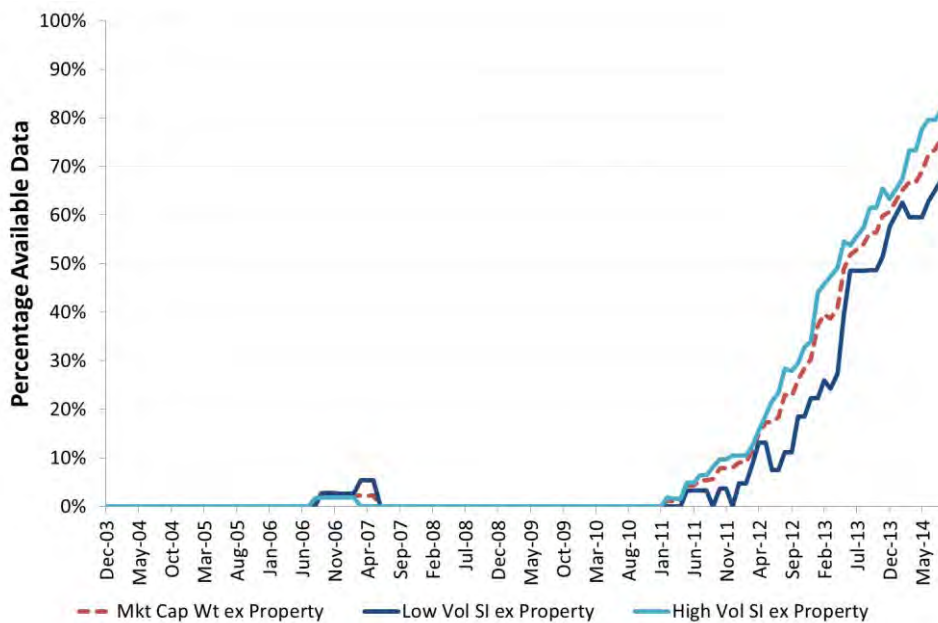
Hsu, Kudoh and Yamada (2013) argue that, although sell side analysts have been shown to display over-optimism regarding firm earnings growth they are still presumably skilled professionals and rational economic agents. Sell-side research can still be valuable and can drive significant brokerage flows. Given that sell-side research can influence client investment activities, analysts are rated and rankings are made public. It is assumed that the analyst research rankings matter to the analysts' employers. Theoretical and empirical research advocate the thesis that forecast accuracy and stock recommendations are linked with analyst promotions and analyst turnover (see Mikhail, Walther and Willis (1999)). Further theories and empirical evidence suggest that relationships with investment banking clients and prospects could influence analysts to bias their earnings growth forecasts upward and set the target stock prices higher than they otherwise would.

In other words, a sell-side analyst could be faced with the situation where they produce favourable earnings growth forecasts without appearing biased and also providing profitable trading recommendations to clients. Hsu *et al.* (2013) argue that there is some equilibrium behaviour where all analysts inflate their reported growth estimates upward (e.g. by half a standard deviation) in order to be investment banking business friendly and to avoid the detection for inflating growth forecasts in certain situations. They argue that this behaviour would predict higher growth forecast bias for firms with higher earnings growth variability. As a consequence, this would also imply higher return volatility for these firms. They found, empirically, high volatility stocks to be associated with high analyst forecast bias. They argue that evidence suggests that investors do not fully appreciate the upward bias present in analyst forecasts; and so they overreact to analyst optimism in the short run. As such volatile stocks tend to be overvalued and experience low subsequent returns. This argument by Hsu *et al.* (2013) would help explain why the analyst growth forecast bias would explain part of the low volatility anomaly.

In the South African setting analyst forecast earnings data is not easily obtainable on a historical basis. Figure 5.4.1 below shows the percentage of stocks in the ALSI 100, high volatility and low volatility portfolios for which 1 year forecast earnings data could be obtained over the back-test period (i.e. December 2003 – August 2014) on Bloomberg.



**Figure 5.4.1: Available Forecast Earnings (December 2003 – August 2014)**



Evidently from Figure 5.4.1 analyst forecast earnings data has been very limited in the South African setting. The analyst forecast earnings data has improved since 2012 such that of the stocks in the ALSI 100 (excluding Property stocks), consensus forecast earnings data was available for 76% of these as of August 2014. Of the stocks in the high and low volatility portfolios 82% and 67% had available analyst forecast earnings as of August 2014.

Consistent with the findings in the earlier section it is evident from Figure 5.13 that the high volatility portfolio has consistently experienced more forecast earnings coverage than the low volatility and market-cap weighted portfolios. However, it is important to note that historically the forecast earnings data has been very limited in the South African market. So testing the analyst forecast earnings bias in the South African setting may not be straightforward given the lack of data.

Hsu *et al.* (2013) define the analyst forecast bias as the difference in the forecast earnings 1 year prior relative to the reported earnings 1 year later.

The forecast earnings growth can be defined as follows:

$$F_{Grow_{t,t+1}} = \frac{F_{EPS_{t,t+1}} - R_{EPS_t}}{|R_{EPS_t}|} \quad (25)$$

where  $F_{Grow_{t,t+1}}$  = forecast *EPS* growth from time  $t$  to  $t + 1$

$F_{EPS_{t,t+1}}$  = forecast *EPS* for time  $t + 1$  at time  $t$

$R_{EPS_t}$  = reported *EPS* at time  $t$

The reported earnings growth is calculated as follows:

$$R_{Grow_{t+1}} = \frac{R_{EPS_{t+1}} - R_{EPS_t}}{|R_{EPS_t}|} \quad (26)$$

where  $R_{Grow_{t+1}}$  = reported earnings growth at time  $t + 1$

$R_{EPS_t}$  = reported earnings at time  $t$

Combining (25) and (26) above the analyst forecast growth bias is defined by Hsu *et al.* (2013) as follows:

$$F_{Grow_{B_{t+1}}} = F_{Grow_{t,t+1}} - R_{Grow_{t+1}} \quad (27)$$

where  $F_{Grow_{B_{t+1}}}$  = earnings growth forecast bias at time  $t + 1$

The aim is to test if there has been a higher forecast earnings growth bias for the high volatility stocks relative to the low volatility stocks in the South African setting. Given the lack of forecast earnings data, this will only be tested over the period June 2013 to August 2014. Using the above derivation the forecast (1 year earlier) and reported earnings (1 year later) will be calculated for each stock in the market-cap weighted, high volatility and low volatility portfolios. Thereafter the average forecast and reported growth for these portfolios will be calculated. This will yield the average forecast and reported earnings growth per stock in the market-cap weighted, high and low volatility portfolios. From this, the forecast earnings growth bias will be calculated for these portfolios. This is shown in Figure 5.4.2 that follows:

**Figure 5.4.2: Growth Forecast Bias between Low and High Beta stocks**

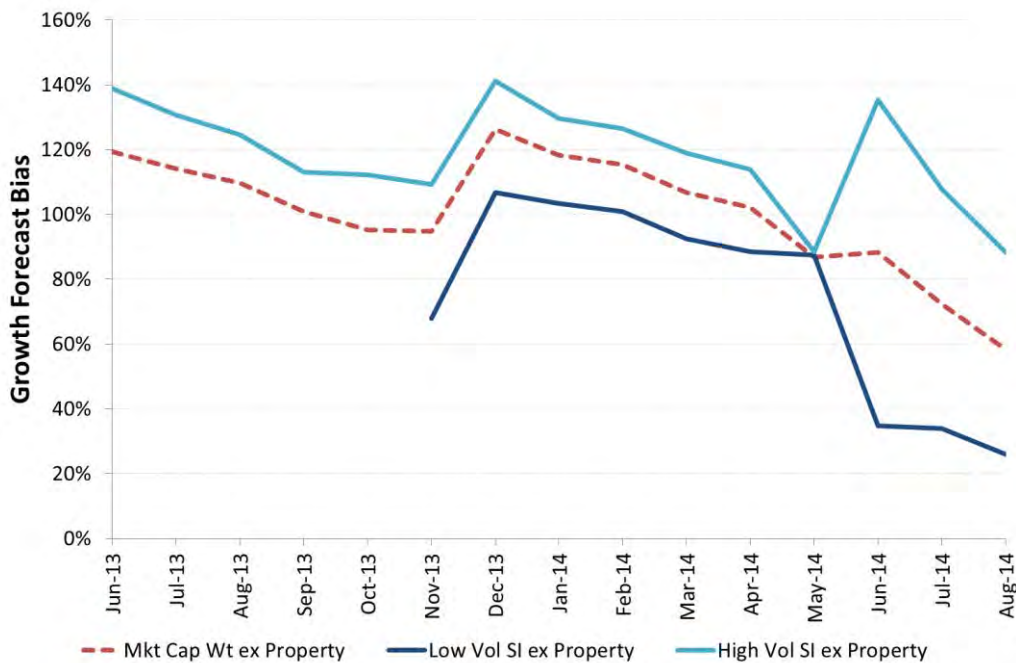


Figure 5.4.2 is consistent with the findings of Hsu *et al.* (2013) that high volatility stocks are associated with high analyst forecast bias. As can be seen, the high volatility portfolio has had a higher forecast bias than the market-cap weighted portfolio. On the other hand, the



low volatility portfolio has had less analyst growth forecast bias than the market-cap weighted portfolio. Hsu *et al.* (2013) argue that evidence suggests that investors do not fully appreciate the upward bias in analyst growth forecasts for high volatility stocks; and so they overreact to analyst optimism in the short run. They argue that this would cause the high volatility stocks to be overpriced leading to lower subsequent returns relative to low volatility portfolios. This helps explain the contribution of the upward growth bias present in analyst forecast earnings for high volatility portfolios to the low volatility anomaly in the South African market.

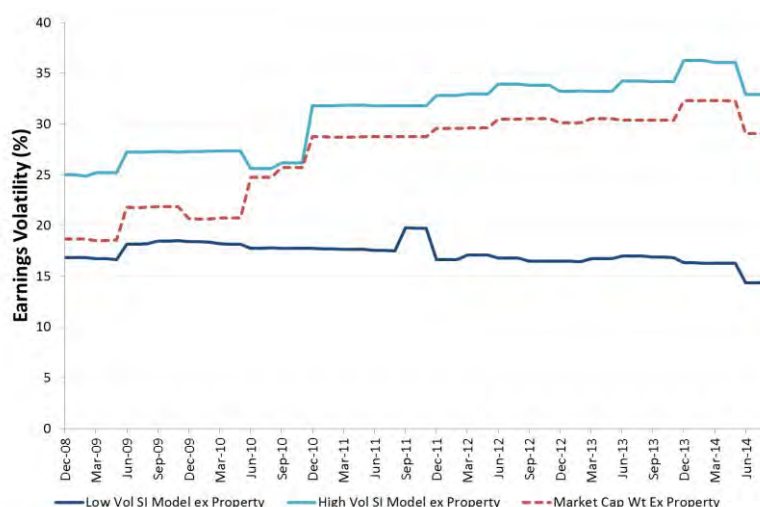
It is important to note that this portfolio only has reliable data from November 2013. A serious criticism of this analysis could be that the analysis period is too short and so very little can be concluded from the analysis. However, it is encouraging to have found the results in the South African market to be consistent with international literature (see Hsu *et al.* (2013)).

### **5.5. Investor overconfidence in growth forecasts for stocks with high earnings variability**

Yamada and Nagawatari (2010) argue that the price volatility of a stock should reflect a company's earnings variability. They found stocks with high earnings variability to also possess high price volatility and vice versa. Hsu *et al.* (2013) also found this relationship to hold in both the developed and emerging markets. In addition, Yamada and Nagawatari (2010) also found stocks with higher earnings variability to have higher earnings growth forecast error than those with low earnings variability. Dichev and Tang (2010) also found that earnings volatility is negatively related to earnings predictability. This suggests that earnings growth of stocks with high earnings variability is harder to forecast than for stocks with low earnings variability. All else equal, this would suggest that the growth forecast of a stock with high earnings variability is more likely to be incorrect than a stock with low earnings variability.

Figure 5.5.1 below depicts the rolling 5 year earnings variability of the low volatility, high volatility and market-cap weighted portfolios that were analysed in the South African setting.

**Figure 5.5.1: Rolling 5 Year Earnings Volatility (December 2003 – August 2014)**

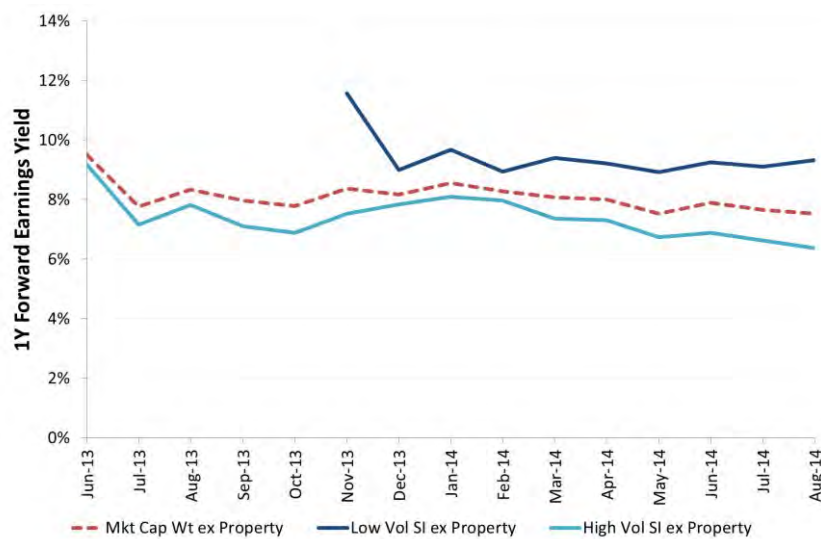


Consistent with Hsu *et al.* (2013), in the South African setting the low volatility portfolio has consistently had lower earnings variability than both the high volatility and market-cap weighted portfolios. According to Dichev and Tang (2010) one would expect the forecast earnings growth of the low volatility portfolio to be more accurate than the high volatility and market-cap weighted portfolios all else equal. In section 4.4 (consistent with Hsu *et al.* (2013)) it was shown that the high volatility portfolio has a higher growth forecast bias than the low volatility portfolio. This combined with the poor earnings growth predictability for stocks with high earnings variability, support the notion that the reported earnings are more likely to miss forecasts for the high volatility portfolio than the low volatility portfolio.

Yamada and Nagawatari (2010) found a positive relationship between earnings variability and price volatility in the Japanese stock market. They found, consistent with Hsu *et al.* (2013), high earnings variability portfolios to exhibit high forecast growth. In addition they found that investors tend to be overconfident in the forecast growth for companies with higher earnings variability. This is reflected in the low forward earnings yield of these companies relative to the low earnings variability counterparts.

Figure 5.5.2 below depicts the forward earnings yield of the low volatility, high volatility and market-cap weighted portfolios in the South African setting. Unfortunately, due to the lack of forecast earnings data this is only reported over the period June 2013 to August 2014.

**Figure 5.5.2: 1 Year Forward Earnings Yield**



In the South African setting, as shown in Figure 5.5.2, the low volatility portfolio has had a higher forward earnings yield than the high volatility and market-cap weighted portfolios. The finding in the South African setting has been consistent with both the studies of Hsu *et al.* (2013) and Yamada and Nagawatari (2010) who found that investors pay a higher premium for the high forecast growth in the stocks with high earnings variability which leads to low subsequent returns for these stocks.

Baker *et al.* (2011) demonstrate that valuing stocks involves forecasting company financials into the future (e.g. revenue growth over the next 5 years etc.) which introduces forecast error. Investors are likely to disagree on their forecasts; in fact the disagreement is likely higher for the more uncertain outcomes (in this case forecasts for high variability stocks). To demonstrate their underlying estimates, investors will either buy or sell stocks. An extra assumption is necessary to connect the differences of opinion to the demand for high volatility stocks that pessimists act less aggressively than optimists, as noted by Baker *et al.* (2011). In other words, investors must be reluctant or unable to short stocks relative to buying them. Given the inability of both individual investors and institutional investors to short stocks, this assumption can be validated. As such stocks with a wide range of opinions will have more optimists among their shareholders and will thus be priced at a premium, leading to lower future returns.

### 5.6. Investor preference for lotteries

Baker *et al.* (2011) use the following gambling example to show the investor preference for lotteries; which they argue is prevalent in the high volatility stocks:

#### Example 5.6.1: Odds of Gamble with \$5 expected payoff

	Lose \$100	Win \$110
Probabilities	50%	50%
Expected Payoff	\$5	

Baker *et al.* (2011) argue that most people would not take this gamble despite the positive expected payoff of \$5. They argue that the possibility of losing \$100 while trying to win \$110 is enough to deter participation.

However, they notice a change in the behaviour if the probabilities and payoffs are shifted although expected payoff remains the same as shown below:

#### Example 5.6.2: Odds of Gamble with \$5 expected payoff

	Lose \$1	Win \$5000
Probabilities	99.88%	0.12%
Expected Payoff	\$5	

They argue that most people take the second gamble, although the expected payoff is the same as that in example 5.6.1. Baker *et al.* (2011) argue that this behaviour is more about positive skewness; where large positive payoffs are more likely than large negative ones than it is about volatility. Yamada and Nagawatari (2010) argue that there are investors who accept low expected returns intentionally in exchange for extremely high returns that are rarely seen. To demonstrate this they focus on the skewness of the low volatility vs. high volatility stocks. Their argument is that high volatility stocks possess positive skewness relative to low volatility stocks. This implies that high volatility stock returns are lower than the mean with a high probability. However, there is a small probability that high volatility stocks can yield exceptionally high returns. Investor demand for this lottery-like payoff leads to high demand for high volatility stocks. This in turn results in lower future returns.

Table 5.6.1 below depicts the skewness of the low volatility, high volatility and market-cap weighted portfolios in the South African setting.

**Table 5.6.1 Skewness of the portfolio returns (December 2003 – August 2014)**

Period	Low Vol SI Model ex Property	High Vol SI Model ex Property	Market Cap Wt Ex Property
3 Months	-0.19	-0.16	0.05
6 Months	-0.02	0.06	0.19
12 Months	0.17	0.28	0.36
36 Months	0.10	0.16	0.22
60 Months	0.09	0.11	0.16
84 Months	0.08	0.09	0.12

It is evident from Table 5.6.1 that the low volatility, high volatility and market-cap weighted portfolios all have positive skewness in their returns. Of these, the market-cap weighted portfolio has the highest positive skewness. The high volatility portfolio exhibits more positive skewness than the low volatility portfolio. The positive skewness inherent in the high volatility portfolio would imply that this portfolio is more likely to deliver returns below the mean; however, there is a small probability that it can deliver abnormal returns. This is consistent with the findings about manager compensation as noted by Baker and Haugen (2012). An investment manager is more likely to earn a performance bonus for returns above a certain threshold if they are invested in high volatility stocks than low volatility stocks. However, they are also more likely to deliver below-average returns.

## 6. Conclusion

### Back-testing the low volatility anomaly in the South African market

In this thesis the low volatility anomaly has been found to be prevalent in the South African market; where low volatility portfolios have outperformed high volatility portfolios at a materially lower risk out-of-period. In addition the low volatility portfolios were found to possess statistically significant positive alphas relative to the high volatility portfolio out-of-period. These findings in the South African market are consistent with international studies (see Baker and Haugen (2012), Hsu *et al.* (2013), Baker *et al.* (2014) among others).

In the South African market the following sector biases within the portfolios were found to explain a statistically significant proportion of the low volatility outperformance:

- Listed Property
  - The low volatility portfolio was materially overweight Listed Property sector relative to the high volatility portfolio.
- FINDI vs. RESI
  - The low volatility portfolio was materially overweight FINDI and underweight RESI shares.

The above-mentioned sector exposures would have benefitted the low volatility portfolio, as it had overweight positions in the sectors that outperformed and underweight positions in the sectors that underperformed. As such it could be argued that the observed outperformance may have been as a result of a sector allocation decision rather than a low volatility anomaly. Thus, the following portfolio construction variations were considered to help gauge if the outperformance observed can solely be attributed to sector effect in the South African market:

- A sector neutral portfolio was constructed to investigate if the observed outperformance could have been as a result of a sector effect.
  - The sector neutral low volatility portfolio outperformed the high volatility portfolio at a lower risk out-of-period and produced a statistically significant positive alpha relative to this portfolio.
  - Thus, it was concluded that the low volatility effect in the South African market exists at the stock selection level within sectors, consistent with Baker *et al.* (2014).
- Portfolios were constructed excluding Listed Property and Resources stocks from the investable universe.
  - The low volatility portfolios outperformed the high volatility portfolios and produced statistically significant positive alphas out-of-period relative to the high volatility portfolios.
  - It was then concluded that the low volatility effect in the South African market is prevalent and statistically significant within sectors; as opposed to it being solely a sector effect.

In the South African market the low volatility portfolios were found to have considerably lower drawdowns than the high volatility and market-cap weighted portfolios. As a result the required positive return burden to break-even (after suffering the losses) was found to be materially smaller for the low volatility portfolios. Consequently, the low volatility portfolios took a much shorter time to recover from losses (i.e. on average 1 year shorter) than the high volatility and market-cap weighted portfolios. As such, the above explanation was found to be prevalent in the South African market and consistent with Blitz and van Vliet (2014).

It was further concluded that the imposition of sector constraints (e.g. sector neutrality) considerably worsened the risk and drawdown characteristics of the low volatility portfolios. In addition the imposition of sector constraints was also found to produce materially different portfolios as shown by the high active share relative to the low volatility portfolios without sector constraints. It was argued that this may have a significant impact on the interpretation of the low volatility anomaly post the imposition of sector constraints. It was then argued that the above findings may help explain why some of the sector-constrained low volatility portfolios underperformed the market-cap weighted portfolio.

### **Understanding the low volatility anomaly in the South African market**

After concluding that the low volatility effect is prevalent and statistically significant within sectors in the South African market, an analysis was performed to help with the understanding of the rationale for the outperformance of these portfolios. In particular the following theoretical explanations were back-tested in the South African market:

#### *1. Benchmarking as a limit to arbitrage (Baker et al. (2011))*

Baker *et al.* (2011) argue that investment managers are typically mandated relative to market-cap weighted benchmarks. From a portfolio construction perspective, Baker *et al.* (2011) show that an investment manager who aims to increase their ex-ante information ratio (relative to the market-cap weighted benchmark) would demand a higher expected alpha from a low beta stock than a high beta stock. It is argued that this would create excess demand for high volatility stocks. Consequently this would lead to high volatility stocks being priced at a premium relative to low volatility stocks, leading to lower subsequent returns. While this explanation was not explicitly back-tested in the South African setting it is closely linked with the explanation regarding manager compensation.

## *2. Manager Compensation and Agency issues between investment managers and their clients (Baker and Haugen (2012))*

Baker and Haugen (2012) and Baker *et al.* (2011) argue that the payoff of an investment manager who is compensated with a performance fee (above a certain threshold) resembles a call option. They argue that the investment manager would maximise the probability of achieving the performance fee if they were invested in high volatility stocks rather than low volatility stocks. This argument was back-tested in the South African market and it was concluded that a manager who is mandated relative to the market-cap weighted benchmark would be taking on unwanted relative risk by investing in the low beta stocks, decreasing their probability of earning a performance fee. On the contrary the manager would be incentivised to avoid low beta stocks and rather invest in high beta stocks to minimise the chances of extreme underperformance on their part. This would induce excess demand for high beta stocks leading them to be overpriced (relative to low beta stocks), implying lower subsequent returns for these stocks. This finding in the South African market is consistent with the international studies of Baker and Haugen (2012) and Baker *et al.* (2011).

## *3. Agency issues amongst investment professionals (Baker and Haugen (2012))*

Baker and Haugen (2012) argue that high volatility stocks receive more analyst coverage than low volatility stocks, implying that they are more likely to be included in the model portfolio than low volatility stocks. This argument was back-tested in the South African market and high volatility stocks were found to have consistently had more analyst coverage than low volatility stocks, consistent with Baker and Haugen (2012). In addition the higher analyst coverage for high volatility stocks was found to have been accompanied by a higher percentage of “Buy” recommendations relative to low volatility stocks. These findings in the South African market strongly support the argument put forth by Baker and Haugen (2012) that high volatility stocks are more likely to be included in the model portfolio than low volatility stocks. This would imply excess demand for high volatility stocks, making them to be priced at a premium relative to low volatility stocks and leading to lower future returns.

## *4. Analysts' Earnings Growth Forecast Bias (Hsu, et al. (2013))*

Hsu *et al.* (2013) found high volatility stocks to be associated with high analyst forecast bias. They argue that evidence suggests that investors do not fully appreciate the upward bias in analyst growth forecasts for high volatility stocks; and so they overreact to analyst optimism in the short run. Hsu *et al.* (2013) argue that this leads to high volatility stocks being overpriced resulting in lower subsequent returns relative to low volatility stocks. In the South African market high volatility stocks were found to have had a consistently higher analyst forecast growth bias than both the low volatility and market-cap weighted portfolios, consistent with Hsu *et al.* (2013). While this does shed some light on the low



volatility anomaly in the South African market, it is important to note that reliable analyst forecast earnings data in this market is only available from November 2013 in Bloomberg. A serious criticism of this analysis could be that the analysis period is too short and so very little can be concluded from the analysis. However, it is encouraging to have found the results in the South African market to be consistent with international literature.

#### *5. Investor overconfidence in growth forecasts for stocks with high earnings variability (Yamada and Nagawatari (2010), Hsu et al. (2013) and Dichev and Tang (2010))*

Yamada and Nagawatari (2010) argue that the price volatility of a stock should reflect a company's earnings variability. They found stocks with high earnings variability to also possess high price volatility and vice versa consistent with Hsu *et al.* (2013). Yamada and Nagawatari (2010) also found stocks with higher earnings variability to have higher earnings growth forecast error than those with low earnings variability. Dichev and Tang (2010) also found that earnings volatility is negatively related to earnings predictability. All else equal, this would suggest that the growth forecast of a stock with high earnings variability is more likely to be incorrect than a stock with low earnings variability. In the South African market the low volatility portfolio was found to have consistently had lower earnings variability than both the high volatility and market-cap weighted portfolios. According to Dichev and Tang (2010) one would expect the forecast earnings growth of the low volatility portfolio to be more accurate than the high volatility and market-cap weighted portfolios all else equal. Yamada and Nagawatari (2010) found that investors tend to be overconfident in the forecast growth for companies with higher earnings variability. This is reflected in the low forward earnings yield of these companies relative to the companies with low earnings variability. In the South African market the high volatility portfolio was found to have had a lower forward earnings yield than the low volatility and market-cap weighted portfolios. The finding in the South African setting is consistent with both the studies of Hsu *et al.* (2013) and Yamada and Nagawatari (2010) who found that investors pay a higher premium for the high forecast growth in the stocks with high earnings variability which leads to low subsequent returns for these stocks.

#### *6. Investor Preference for lotteries (Baker et al. (2011))*

Baker *et al.* (2011) argue that the low volatility anomaly can be attributed to behavioural biases regarding positive skewness; where large positive payoffs are more likely than large negative ones than it is about volatility. Yamada and Nagawatari (2010) argue that there are investors who accept low expected returns intentionally in exchange for extremely high returns that are rarely seen. Yamada and Nagawatari (2010) further argue that high volatility stocks possess positive skewness relative to low volatility stocks. This implies that high volatility stock returns are lower than the mean with a high probability. However, there

is a small probability that high volatility stocks can yield exceptionally high returns. In the South African market the high volatility portfolio was found to exhibit more positive skewness than the low volatility portfolio, consistent with Baker *et al.* (2011) and Yamada and Nagawatari (2010). The positive skewness inherent in the high volatility portfolio would imply that this portfolio is more likely to deliver returns below the mean; however, there is a small probability that it can deliver abnormally high returns. Yamada and Nagawatari (2010) argue that investor demand for this lottery-like payoff leads to excess demand for high volatility stocks, resulting in lower future returns. The above finding in the South African market supports this argument by Yamada and Nagawatari (2010).

In conclusion the low volatility anomaly was found to be prevalent in the South African market. The findings in international literature regarding the potential causes of the anomaly were also found to be prevalent in the South African market. Given the causes and market biases (e.g. analyst forecast biases etc.) that have been covered in this thesis continue into the future, the low volatility anomaly can be expected to continue in the South African equity market.

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